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SUPPORTING INFORMATION RETRIEVAL FROM CLINICAL NARRATIVE TEXTS USING TEXT CLASSIFICATION AND VISUALIZATION TECHNIQUES

BY

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DECLARATION

I hereby declare that this thesis is my own work of the research I undertook as partial requirement towards attainment of the Doctor of Philosophy and that to the best of my knowledge (except where due acknowledgement has been made in the text), it contains no material which has been accepted for the award of any other degree in this or any other University. I hereby certify that the work presented in this thesis is my own and that work performed by others is appropriately cited.

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This thesis has been submitted as a partial fulfilment of requirements for the Doctor of Philosophy degree in Computer Science of the University of Nairobi with our approval as the University Supervisors.

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DEDICATION

I dedicate this thesis to my loving and supportive family. My wife Juliet Moso and my children; Jeremy Kipchumba, Jared Kimutai and Jemimah Cheberur have been a continued source of encouragement, and have shown tremendous patience with me throughout all the long hours and nights. My parents late Nelson Kipkenei Koech and Esther Teriki Kenei, my parents' in-law Francis Moso and Esther Moso have provided inspiration and encouragement for which I am very grateful.

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ABSTRACT

Electronic health records (EHRs) are increasingly becoming common in healthcare delivery settings, enabling physicians to continuously document patients' care episodes in EHRs and therefore creating digital health records of individual patients. This along with general advances in software and computer hardware has made it increasingly easy to capture and store patient clinical data electronically which has, in turn, yielded an increasing supply of readily available patients' clinical information in electronic health records. However, retrieving clinical information from long clinical narrative texts is a challenging problem. Clinical narrative texts provide significant difficulties for conventional natural language processing techniques when it comes to retrieving information from long clinical text documents. Additionally, a detailed assessment of past studies revealed a lack of theoretical support for the computational techniques employed, and a scarcity of research on information retrieval techniques applicable to clinical narrative texts. Most clinical information is in narrative text form which limits users from quickly finding desired information given the large volume of texts that needs to be read. A physician's capacity to read and get information from text for clinical overview is severely affected when records get longer. Thus, medical practitioners are increasingly confronted with information flood which provides more information than practitioners can process especially in time constraint healthcare delivery settings. Physicians still use a standard linear text layout in computer screens which one must read through the same way one would their paper counterparts. Thus, the challenges experienced by physicians in navigating, retrieving, and synthesizing paper-based patient records remain unsolved with current electronic health systems. This makes the process of identifying the most critical and significant nuggets of clinical information in a given patient clinical record challenging but worthwhile task. Due to the continuous growth of clinical data, automated retrieval of important pieces of information from clinical narrative text is becoming an important research problem.

In this thesis, we proposed text classification and visualization model to support information retrieval from clinical narrative texts in electronic health records. The objective of this study is to overcome the challenges encountered in retrieving information from clinical narrative texts. In our approach clinical narrative texts are classified into different class orientations and then visualized as a cluster map. A set of five information facets were identified to characterize relevant facets of information. We developed a deep learning algorithm to classify clinical narrative texts into a predefined set of classes. From the state of art, it was

found out that training deep learning models is difficult, and getting them to converge in a reasonable amount of time is still challenging. To overcome this problem, we proposed a novel layer normalization technique called range normalization which outperformed conventional techniques. An artefact was developed and user study was conducted to collect feedback from healthcare practitioners on the usefulness of such a tool in supporting information retrieval from clinical texts. The results showed that such a model would be useful to physicians in reviewing clinical narrative texts especially for patients with lengthy medical histories. The results from the study show that the artefact is useful and effective in supporting physicians during care episodes. The results suggest that integrating visualization into an electronic health record would be beneficial to physicians in satisfying their information needs. Modelling texts into meaningful information facets provides organized clinical narrative text documents.

Keywords-visualization; classification; information retrieval; electronic health records;

DEFINITION OF TERMS

Machine Learning (ML) - A subfield of computer science and statistics that teach computers to make decisions on data provided for them.

Supervised Learning - A machine learning technique which provides labelled data to algorithms to 'learn' from.

Natural Language Processing (NLP) – Use of computational methods to extract information from spoken or written language by humans.

Deep Learning –Artificial neural network with multiple layers.

Personally Identifiable Information (PII) - Information that can uniquely identify an individual, such as full name, address, date of birth, and telephone number.

Narrative text – Refers to narrative textual information expressed as phrases, sentences and paragraphs.

Structuring - Organising information according to a logical model which is meaningful to humans or computers or both.

Patient encounter – Interaction between a physician and a doctor during healthcare delivery.

Text categorization - Grouping narrative text into thematic categories.

Word embeddings – A technique for representing words using real valued vectors.

Data visualization- Representing data in a visual context, such as a map or graph.

Sentence embedding – A technique for representing sentences by mapping to sequences of numbers that represent their meaning.

Confidentiality - Obligation of medical professionals not to disclose patient information; codified in the Hippocratic Oath in the 4th century BC.

Privacy - Protecting an individual's control on what personal information may or may not be shared with others.

Health data - Data which is associated with the provision of healthcare services to patients

Structured data - Data with organised structure.

Unstructured data – Data in form narrative text

Discharge summary- A clinical report produced at the conclusion of a hospital stay.

Text classification - A supervised machine learning method used to classify sentences or text documents into one or more defined categories.

Cognitive Load - The sum mental effort required to solve a problem.

LIST OF ABBREVIATIONS AND ACRONYMS

BN	-	Batch Normalization
CDA	-	Clinical Document Architecture
EHR	-	Electronic Health Record
EMR	-	Electronic Medical Record
PII	-	Personal Identifying Information
I2B2	-	Informatics for Integrating Biology and the Bedside
ISO	-	International Organization for Standardization
HIDE	-	Health Information DE-identification
MIST	-	MITRE Identification Scrubber Toolkit
HIE	-	Health Information exchange
HIE	-	Health Information Exchange
ICU	-	Intensive Care Unit
CRF	-	Conditional Random Field
RNN	-	Recurrent neural network
SOAP	-	Subjective information, Objective information, Assessments and Plan
SVM	-	Support Vector Machine
MeDS	-	Medical De-identification System
HMIS	-	Health Management Information System
WHO	-	World Health Organization
UMLS	-	Unified Medical Language System
POMR	-	Problem-oriented Medical Record
NER	-	Named Entity Recognition
NLP	-	Natural Language Processing
HL7	-	Health Level Seven
ICD	-	International Classification of Diseases
BOW	-	Bag-of-words
LSTM	-	Long Short-Term Memory
GPUs	-	Graphics processing units
CNN	-	Convolutional neural networks
ReLU	-	Rectifier linear unit
TF-IDF	-	Term Frequency Inverse Document Frequency

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CHAPTER ONE: INTRODUCTION

In this chapter, we give an introduction of electronic health records and then present a detailed background and the challenges of using electronic clinical narrative texts in electronic health records (EHRs) in healthcare delivery setting. Then we describe various text analytic techniques and highlight how it can support information retrieval from clinical narrative texts in electronic health records.

1.1 Overview

The prevalent use of electronic health records is common in healthcare today; however, information overload coupled with rapid accumulation of large volumes of clinical narrative texts have threatened the effective use of electronic health records. During daily encounters with patients, physicians are required to read, understand and get a summarized comprehension of earlier clinical documentation for the patient at hand. The documentation is majorly unstructured narrative texts that provide significant information over and above structured counterparts (Kvist et al., 2011). Most of the patient information describing the patient's healthy history is presented in narrative texts. Therefore, a lot of clinical narrative texts are generated during care episodes with a lot of information that can overwhelm the cognitive load of physicians when seeking for information. In many clinical situations, medical practitioners are required to, within a short time, understand a patient medical history. In addition to talking with and examining the patient, doctors rely on medical records in EHRs for medical history. One of the problems in this process is the availability of detailed electronic information. This information was earlier limited in paper records, but with electronic health records, there is a lot of detailed information about patients, mostly in clinical narrative texts (Ling, 2017). However, the unstructured nature inherent in clinical narrative texts and information overload problem makes it difficult for physicians to use available digital clinical information. Physicians are therefore mostly unable to review much of this information during clinical encounters due to the abundance of texts and the time constraint inherent in the clinical setting (Liang, Tsou and Poddar, 2019). Information retrieval from narrative texts is therefore very challenging, especially for clinical decision support and knowledge discovery. Primary care physicians face cognitive overload daily, due to patients 'clinical documentation mostly in narrative texts (Koopman et al., 2015). Finding relevant clinical information in long and rapidly growing patients' medical histories is challenging. Electronic health records have made large volume of patient data at the physicians' disposal. One natural way of tackling this is searching for information, by taking a look at a document, discovering relevant sections, and then focusing on a particular section to obtain information. However, the unstructured nature of narrative texts makes it difficult to identify the relevant sections at a glance. In such a case selective reading, where users are able to only read texts with the information of interest instead of running through a whole document could be helpful. This can be achieved by segmenting a given text document into a set of coherent information facets.

In healthcare delivery, most significant patients' patient's medical information is generated in form of clinical narrative texts during care episodes. These notes are useful in making healthcare decisions requiring extraction and retrieval of relevant clinical information from these texts. However, their use in clinical care is challenging due to their unstructured nature (Assale et al., 2019) and information overload (Rand et al., 2018) occasioned by availability of large volumes of narrative texts. Because of the widespread use of electronic health systems, there is now an abundance of clinical data that can be used to improve healthcare. At the same time, it has led to "information overload" problem, that makes it challenging for physicians to use this repository of data e.g., finding the right piece of information in long clinical texts. From the literature, current electronic health systems lack tools for synthesis and analysis of clinical narrative texts, generation of summaries, and efficient information retrieval for its increasing electronic narrative texts. This negatively affects physicians in providing effective patient care especially with patients requiring synthesis of multiple clinical elements in a long patient clinical history. Documenting clinical encounters is popularly done using narrative text due to its expressive and flexible nature (Sultanum et al, 2018) providing an intuitive way for physicians to write patients' clinical patient information.

In addition, narrative text is preferred because it's memorable and expressive and can therefore be used to comprehensively document patient information during clinical encounters (Loudon, 1993) and to facilitate temporal and analytical reasoning (Greenhalgh, and Hurwitz, 1999). There is always some important information that is written by physicians using narrative notes that can't be expressed using structured health records.

The disadvantage of clinical narrative notes is the manual review process required to find relevant clinical information, which is well known to be time consuming and laborious (Wiggins, 2019), (Reichert et al., 2010). In a typical healthcare delivery setting, healthcare delivery process generates lots of patient clinical data continuously, requiring physician's attention, to make decisions based on different types of data for different patients (Manor-Shulman et al., 2008). To review a patient clinical record, physicians have to read patients' clinical records in order to obtain relevant clinical information. An efficient way to look for particular information would be to browse through categories of information rather than reading through the entire text record. In order to achieve this, there is need to segment a given clinical text document into semantically coherent categories. In the past, there has been a growing need in the medical community for clinical NLP techniques to support retrieval of useful information from clinical narrative texts to support clinical decision-making (Kim, Riloff and Meystre., 2011). A number of computational approaches such as clinical text classification and visualization have been proposed in the literature to handle these challenges. These techniques, help in extracting valuable clinical information and reducing cognitive overload. Research on the above techniques and their contribution on clinical decision support, is still lacking. In this thesis we aimed at bridging this gap by investigating the application of text classification and visualization in supporting information retrieval from clinical narrative texts.

In this thesis design and presented an artefact to address the challenges in using clinical narrative texts using two approaches;

i. Text classification to classify clinical narrative texts into distinct information facets. We applied text classification to label atomic sentences/phrases in a narrative text into various relevant information classes.
ii. Text visualization to help visually present the classified narrative texts according to their information classes using cluster map structure.

We present our approach and describe an artefact implementation with possible use cases while highlighting it can support information retrieval from a patient clinical narrative chart. By offering five facets of granularity, the proposed artefact provides a multi-faceted view of a patient medical chart, showing the inherent relationships between different information facets. The proposed artefact affords physicians access to detailed clinical information of a given patient without reading the entire chart. To achieve this, we employed text classification algorithm, the core component of the artefact to classify clinical texts into four SOAP documentation format classes; Subjective, Objective, Assessment, and Plan. In addition a fifth class containing personal identifying information was included. Because of the need to maintain patient privacy and confidentiality, we anonymized the information classified as personal-identifying information. In quest of gaining visual overview of clinical texts, we used texts labeled by the classifier to generate a visual map using different facets of a clinical narrative text in a cluster map.

Our work shows that it is possible for computer systems to generate effective visual clusters of complex clinical textual documents. The proposed model can more effectively cluster clinical information in medical text chart, thus helping doctors in information seeking and hence improving patient care.

We evaluated our proposed clinical document classifier based on convolutional neural network with sentence embedding with residual connections and range normalization against other baseline algorithms. Results show that our classifier convergences faster during training compared to other models. After about 20 epochs, training can achieve a steady state with a smooth loss curve and high accuracy. On clinical sentence classification tasks, we also tested the proposed model against baseline models, achieving better or comparable results. We then evaluated the artefact practical usability, and received positive feedback from respondents.

Our major contributions are enumerated below:

i. A theoretical definition of the problem's domain: information overload and cognitive load need to be addressed to support information retrieval from clinical narrative texts.

ii. The definition of an automatic information visualization generator based on SOAP documentation format. Through this approach visualizations can be generated based on SOAP documentation predefined sections.

iii. Classification and visualization of clinical narrative texts using sentence embedding and deep neural network with residual connections and range normalization.

iv. The use of range normalization to accelerate and stabilize deep neural network training. This is, to the best of our knowledge, the first-time range normalization has been used.

v. A semantic labelling to create a semantic representation of the text and grouping to form clusters of related sentence fragments.

vi. The creation and implementation of a proof-of-concept artefact from the findings of this research.

Our proposed solution is expected to support information extraction and retrieval tasks by organizing clinical notes into meaningful facets that correspond to physician's relevant information needs. We based our classification and visualization on SOAP documentation format sections. Classifying texts into their various classes helped us organize and visualize clinical notes according to SOAP sections texts allowing related texts to remain together. The proposed technique presents clinical narrative text by organizing them into an intuitive and useful cluster map, thus supporting physicians gain quick and easy access to important medical information.

1.2 Background

1.2.1 Electronic documentation and medical records

In our contemporary digital society, we live amidst a mass of electronic documents in different domains. Retrieving information from these documents is highly desirable but extremely challenging due to their unstructured nature. The increasing availability of such electronic documents increases the need for automated methods to help extract and retrieve the needed information to support decision making. Usually, these documents are useful in conveying information, sharing knowledge, coordinating activities, as well recording business activities. This is also true for health information, which exists in various health-information systems, such as electronic health records (EHRs). In many application domains, users are often required to obtain information from large volumes of texts in order to get some information to support decision making. For instance, in healthcare domain physicians must review a number of patients' clinical records in order to make appropriate decisions. In this case, a physician must read the entire medical chart to see what happened longitudinally over the patient's hospitalization in order to compile the discharge summary. In many cases, this requires one to read and understand the whole text in order to get the required information which is a challenge for time-critical tasks that need quick review of large amount of data, e.g., in intensive care unit (ICU). Thus, there is need for novel techniques that can facilitate quick information retrieval and presentation to support information synthesis.

In the health domain, electronic health records and other technologies have become increasingly common in clinical practice (Bush et al., 2018; Boonstra, Versluis and Vos, 2015) and this has led to increased number and size of available clinical data sets (Tang, F 2018), (Jensen, Jensen and Brunak, 2012) and increased physicians' access to detailed patient information (Edinger, 2014) in electronic health records. The increased access to large volumes of electronic data however has not led to increased availability of information (Hanauer et al., 2015). Increasingly healthcare facilities are relying on information stored in electronic health records for efficient healthcare delivery and thus the demand for data analytics techniques to support this pressing need (Liu et al., 2017) has increased.

According to Healthcare Information and Management Systems (HIMSS) definition model (2003), the ideal functions supported by EHRs include; supporting input and management of patients' episodic and longitudinal medical information thus providing physicians a repository of primary information during the provision of patient care. They create a complete record of a clinical encounter with patient and this coupled with the increasing health information exchange between healthcare facilities has also resulted in unique longitudinal data that describes patients' clinical trajectories (Borland, Hammond and West, 2016). This results in unprecedented volumes of patient data mostly in form of clinical narrative texts that are available in electronic health records at the physicians' disposal. Increasingly, healthcare facilities have access to this data through computers (Johnson, 1999). With the prevalent use of electronic health records in many countries, unprecedented amounts of patient information will be readily available at physicians' workstations (Fragidis et al., 2018). The same information also will be readily available to researchers to gain access to rich data sets for clinical research (Gehrmann et al., 2018). The same clinical documents are also becoming available to researchers for use in developing resources and tools that may help clinicians in their work (Orosz, Novák and Prószéky, 2013). Using this electronic health records has improved research in healthcare by providing clinically relevant datasets cheaply. And this means that medical practice and research are increasingly in need of data analytic approaches to help analyze the generated datasets (Zillner et al., 2008).

The availability of granular and redundant information with patients living with chronic conditions who require frequent in-and out-patient treatment is now very common (Kreuzthaler et al., 2019). Such clinical documentation is mostly expressed in natural language (Roberts, 2017), (Denny et al., 2009), and exists in narrative text form such as clinical notes (Murdoch and Detsky, 2013), and contains a wealth of information, documented in narrative texts (Reichert et al, 2010; Harkema et al, 2005), but having to sift through it, is a daunting task. Although there is a lot of useful information available for each patient in electronic form, this information is not optimally organized for efficient use in patient care (Franz, Schuler and Helm, 2013). During care episodes, medical documents are generated and stored in EHRs, often in narrative text form. The increasing availability of such documents calls for an effective technique for timely retrieval of information (Spat et al., 2007) to support clinical decisions. For example, ability to recognize medical concepts in clinical narrative text is a key component of biomedical information retrieval systems (Arbabi et al., 2019) and useful in applications such as in analysis of narrative clinical texts in electronic health records (Jonnagaddala et al., 2017), (Luo et al., 2017).

In an electronic health record, patient clinical records are usually recorded as a sequence of healthcare visits and the record in each visit can be classified into different information facets such as demographics and the patient clinical profile (Ashfaq, 2019). Demographic part includes names, age, gender, place etc. On the other hand, the clinical profile has narrative text describing details such as symptoms, diagnoses, disease/conclusion and treatment recorded during patient visit. This has led to massive availability of digital clinical narrative text documents (Wang, Xu and Uzuner, 2019), (Carell et al., 2014). Enhancing access to this wealth of information could serve a number of purposes (Harkema et al., 2005) such as supporting patient care and secondary purposes such as clinical and translational research (Liu et al., 2019), (Wang et al., 2018). In addition to primary use for direct clinical care, these systems are increasingly becoming a valuable source of data for “secondary purposes,” such as clinical research (Shickel et al., 2018), (Safran et al., 2007) and epidemiological studies (Carell et al., 2014). Electronic health records are therefore generating large datasets which can be useful for research (Deléger et al., 2017) with the potential of improving the overall healthcare delivery. This is dependent on the accurate and complete retrieval of the relevant patients’ cohorts, which is in narrative text (Edinger et al., 2017) that represents a rich source of patient health data (Ni et al., 2019). In addition, the various uses of generated data require the ability to find the desired complete information accurately (Edinger, 2014). In a typical health-care system, there are a number of patients seeking health services and the amount of data that can be collected and stored in EHRs can be enormous. Leveraging this data for secondary purposes can benefit both the local and national healthcare systems (Edinger et al., 2019).

From the literature, there are many machine learning techniques which have been proposed to process data in electronic health records (Sheikhalishahi et al., 2019). However, most of the clinical data is in narrative text (Jensen et al., 2017), which poses challenges in information extraction (Wang et al., 2018) and information retrieval (Edinger et al., 2017) and thus making it difficult to easily locate important clinical information like symptoms, diagnosis, disease and treatments (Edinger et al, 2017) in a given clinical document. A good example is the difficulty of finding key sections such as Assessment and Plan in the resulting note in a clinical document written using SOAP documentation format (Huang et al., 2018).

Clinical narrative texts contain useful information describing patients’ clinical histories. Clinical notes for example, contain detailed information about health states of patients for each of their encounters with a healthcare system (Bai and Vucetic, 2019). Thus, the rapid growth of electronic clinical documents has created the need for tools to help traverse long documents thus facilitating accurate and timely information retrieval (Patrick and Li, 2010) and providing a complete picture of a patient’s medical history, diagnosis, treatment, and outcome. As healthcare facilities continue to use electronic health records, their ability to navigate the health histories of patients becomes even more crucial. Finding vital pieces of information is critical to developing an assessment and treatment plan for individual patients.

However, medical records are mostly unstructured documents, impeding easy retrieval of information (Laforest and Verdier, 2007) and this requires information extraction systems which accurately and quickly retrieve information often under time constraint situations which is inherent in healthcare delivery (Patrick and Li, 2010). Despite the many benefits associated with electronic health systems (Edinger, 2014), it is still challenging to use it due to information retrieval challenges (Lelong, 2016), (Patrick and Li, 2010). Currently, there is a lot of information which is available in narrative form and in most cases; useful documents are large, so users have to rely on traditional search technique in order to obtain desired information (Lu and Liu, 2011). Traditional keyword search techniques are not always transparent to users (Dridi and Ahmed, 2015). Besides, the result of a search process is always a linear list presentation which can sometimes be long. In addition, the relationships and connections between concepts are never illustrated (Dridi and Ahmed, 2015).

The unprecedented increase in clinical data (Raghupathi and Raghupathi, 2014) has therefore created new opportunities and challenges (Wolfe, Chisolm and Bohsali, 2018), (Adibuzzaman et al., 2018), (Clynch and Kellett, 2015), (White, 2014), (Ching et al., 2018). Opportunities of leveraging the stored data for secondary purposes such as phenotype extraction (Cohen and Elhadad, 2013), design of risk prediction models using electronic health records (Goldstein et al., 2016), (Rajkomar et al., 2018) and challenges such as retrieving information from unstructured narrative texts (Assale et al., 2019).

The primary source of valuable clinical information is electronic health records; however, accessing key information is a time-consuming and inefficient process (Reichert et al., 2010). The time spent by physicians in accessing and also documenting patient information using electronic health records during clinical encounters is often too long and is also becoming a usability concern (Zhang et al., 2010). Intensive care units (ICUs) for example, monitor critically ill patients which generates a lot of data (Zalewski et al., 2017) which requires the attention of physicians and this is challenging for them to use such large volumes of high-dimensional data when diagnosing and treating patients (Zalewski et al., 2017). The problem of chronic diseases is also presenting similar challenges as a result of large volumes of data which are collected to treat individuals with chronic diseases such cancer (Backonja, Haynes and Kim, 2018). Managing patients with chronic diseases requires this same processing of enormous volumes data accumulated over time (Klimov and Shahar, 2005). Due to the unstructured narrative form of clinical documents (Farri et al, 2012), synthesis is a time-consuming and error-prone process that requires reading through the text. This therefore has created new challenges for computer science to provide adequate tools for data exploration techniques such as text visualization (Noone, Warren, & Brittain, 1998) which is the topic of this thesis. Recent studies point out that, there are still some open challenges that need computer scientists and medical practitioners to address in order to realize the potential of unstructured narrative notes that is generated in hospital settings and stored in electronic health records (Assale et al., 2019).

Electronic health records generate many clinical text documents such as clinical notes, prescriptions, and discharge summaries etc., which reflect different aspects of patients' clinical events (Rosenbloom et al, 2010). Using this information presents a number of challenges, including information redundancy inherent in texts and large volumes of readily available documents. These documents are typically a continuous documentation of care episodes in form of clinical notes (Moen et al, 2016), and physicians document a lot of important information for various types of encounters within these clinical notes. This information usually keeps on growing as patients seek medical services, which makes it challenging for physicians to review and understand clinical events of a patient timely and efficiently. This is especially the case for patients with long medical histories particularly in our contemporary society where the prevalence of chronic diseases is on the rise (Sheikhalishahi et al., 2019), (Bashyam et al., 2009), (WHO, 2014), (Pivovarov and Elhadad, 2015). For example, most chronically ill patients often have a lot of records which are challenging to coherently present (Christensen and Grimsmo, 2008). In chronic disease care, clinical data is collected over a long period of time which needs physician attention during care episodes. A practical example is given by Pivovarov and Elhadad (2015) of a kidney problem which is a common prevalent chronic condition. In their study, patients had an average of 338 notes collected across all clinical settings over a period of fourteen years, "with several patients' records containing over 4000 notes". In such a case, it is evidently clear that In the course of a typical medical appointment, it is difficult for a doctor to read hundreds of clinical notes. (Pivovarov and Elhadad, 2015). Clinical decision-making requires access to just relevant patient data (Deng and Denecke, 2014).

However, according to (Laxmisan et al., 2012) several available commercial EHR systems have inadequately addressed this important pressing need, the need for effective techniques to retrieve and present data collected in electronic health records (EHRs) (Wang et al., 2011). Some researchers argue that, EHRs provide detailed and organized data with no functionality to synthesis the available information (Laxmisan et al., 2012). As the use of electronic health records become more common, the need for effective techniques to process its data becomes more pressing (Wang et al., 2011). Despite their widespread use, electronic health records

(EHRs) are still understudied when it comes to supporting information retrieval (Colicchio and Cimino, 2019). Most health information systems have not yet reached their full potential as electronic information sources, since clinical data isn't organized to lessen the effort required to extract and retrieve the required information. There is a need for systems that allow physicians to quickly retrieve various types of medical information, such as symptoms, diagnoses, and so on (Ruan et al., 2018). Reichert et al (2010) argues that "electronic health records (EHRs) are effective in capturing and storing information, but lack the means to aggregate or synthesize the available data for a given patient, especially when it comes to the information conveyed in the notes themselves") and therefor makes it difficult for doctors to differentiate relevant information from irrelevant or duplicated information (Reichert et al., 2010). Further research is required to investigate approaches for capturing and representing clinicians' reasoning and improving information retrieval (Colicchio and Cimino, 2019). Several literature recommendations, such as the World Health Organization's (WHO) and Global Action Plan (2013) (Dorr et al, 2007), strongly support the use of Health Information Technology to improve the outcomes and quality of care for people with chronic conditions. However, according to the literature, it has yet to support the unique information-based processes required for improving chronic illness care (Dorr et al., 2007; Samal et al., 2011). Patients with chronic diseases may visit a healthcare facility several times in a year, which results in massive clinical documentation (Christensen and Grimsmo, 2008). If data is not presented in a friendly, concise, and coherent format, a busy clinician may be burdened by a large number of patient electronic health records. Furthermore, they may not have enough time to read everything, but in many cases, they must make critical decisions based on their understanding of the available clinical records. This, combined with usability concerns about health information technology (HIT) adoption (Yen and Bakken, 2012), particularly electronic health records (EHRs) (Mazur et al., 2019), (Arndt et al., 2017), and (Ratwani et al., 2015a), may impede widespread adoption of EHRs. According to Meyer (2010), the time required to review electronic health records is a significant challenge for healthcare providers (Han and Lopp, 2013), (Jain et al., 2012), (Lamberts, 2012), (Craig and Farrell, 2010). The majority of information stored in medical information systems does not support physicians' cognitive processes (Bui, Aberle and Kangarloo, 2007). Thus, efficient tools such as text visualization are needed to help process clinical documents thus improving physicians' cognitive workload and performance (Workman, Lesser and Kim, 2007). Text visualization, according to Alharbi and Laramee (2019), is a subfield of information visualization and visual analytics that is growing exponentially due to the increasing availability of digital text in various forms, such as web pages, blogs, twitter, email, electronic publications, and digitized books. Its goal is to extract key knowledge from text collections that have been digitized (Alharbi and Laramee, 2019). It is an emerging text processing subfield that has shown significant promise in addressing information overload challenges, such as in the healthcare domain (Cao and Cui, 2016a). According to Ware (2004), information visualization (Infovis) is useful because it can identify and visually distill the most valuable and relevant information content from large sets of data, allowing users to browse and comprehend vast amounts of information. In clinical practice, research has shown that visual graphical summaries of patient information result in faster and more accurate medical diagnoses, thereby improving healthcare quality (Forsman et al., 2013). (Torsvik, Lillebo and Mikkelsen., 2013). According to (Singh, Zerr, and Siersdorfer, 2017), understanding the content of large text corpora can be a difficult and time-consuming task. The size and complexity of clinical documents may make it difficult to gain a comprehensive understanding of a patient's history. As the amount of document information continues to grow, tools that can assist in navigating the massive text documents and efficiently acquiring useful information and knowledge are desperately needed. There is a need for systems that can help organize and navigate patient data in a way that improves a clinician's ability to understand information and thus efficiency (Bashyam et al., 2009). Furthermore, the traditional method of extracting information from clinical charts is time-consuming and poses inherent risks to patient privacy, limiting the amount of data available for research (Carell et al., 2014). The confidentiality of clinical data has always been a critical issue for the research community in order to develop computational tools to analyze such data (Zhang and Patrick, 2007). As previously stated, physicians are frequently required to make critical medical decisions that may be based on a patient's previous health history and often necessitate extensive manual review of clinical notes in order to understand a patient's health history (Grasso, Joshi and Siegel, 2016). It is important to easily retrieve the most clinically relevant data from a patient health record and make it readily available to physician without the need for manual chart review. As a result, it's critical to create computational tools that present available patient clinical documents in an easy-to-read and understand format, and they should be accessible via widely used modalities to encourage widespread use. The abundant availability of large clinical data sets due to increasing use of electronic health records (Assale et al., 2019) coupled with increasing advancement in machine learning and information visualization offer great potential to leverage this information to advance healthcare delivery and research. A promising approach is to leverage unprecedented amounts of healthcare data generated and stored in Electronic Health Records (EHRs) and Machine Learning (ML) tools to support clinical decisions and research and hence advance medicine (Asfaq, 2019).

According to Gupta et al (2018), medical history in electronic health records can be leveraged using data analytic techniques for various clinical applications such as diagnosis, precision medicine etc. According to Chittaro (2001), information visualization (InfoVis) can facilitate the use of available medical data by presenting it in intuitive, understandable, recognizable, navigable, and manageable formats, which in turn can help users to quickly extract useful information from medical records. An accurate classification of clinical facets of information in clinical documents and visualization using intuitive visual display could help address the aforementioned challenges.

In medical practice, physicians should be able to retrieve complete and accurate patient information from a patient medical history during consultation (Sultanum et al, 2018) or emergency intervention (Hassanzadeh et al, 2018) such as the case of emergency cases in hospitals with overcrowded patients with various severe health problems (Lucini et al., 2017) thus making it crucial to develop tools to extract such information from clinical texts. In particular, designing systems that can be able to classify and visualize the multifaceted clinical information has the potential to significantly enhance the use of available digital clinical documentation. It has been found out that data visualization (DV) is useful in dealing with multifaceted data and presenting information in a user-friendly way (Chen, 2013).

The full patient history can be visualized to display multiple facets of information. This can then support physicians in seeking information from different information facets. For example, physicians read thousands of patients' clinical narrative texts every year. They suffer from information overload which is a well-known problem and serious when one needs to make decisions or understand some issues deeply, which typically involves reviewing several documents within a limited time period (Shickel et al., 2018). On the other hand, clinical notes are crucial for clinicians who need to review these notes, summarize data, and create treatment plans for patients in a timely (Sieja et al., 2017).

1.2.2 History of medical records

The medical record has been in existence for many centuries. It is believed that it was introduced by Hippocrates in the fifth century B.C (Al-Ghamdi, 2003) and it is a powerful tool which contains patients' previous health conditions and treatments (Winslow et al., 1997). Medical records can be described as archives of patients' clinical information and is used to support patient care (Ruan et al., 2018). It helps physicians to track their patients' medical histories and identify potential issues for diagnosis (Winslow et al., 1997). Hippocrates greatly influenced medical documentation by advocating that the patient health record should serve two purposes; "It should accurately reflect the course of the disease" and "Indicate the possible causes of the disease" (Bemmel, Musen, & Helder, 1997). A medical record usually gives an account of a patient's clinical events and serves an important role in patient care. Its main purpose is to help physicians in healthcare delivery (Al-Ghamdi, 2003) by providing information needed for direct clinical practice (Tange et al., 1998). It was originally used as a reminder for the individual doctor, but has evolved into a communication tool used by different professionals who share responsibility for an individual patient (Tange et al., 1998).

Electronic health records have become increasingly popular in recent years, and various studies, such as Burke et al (2015), have empirically proved their benefits in healthcare delivery. They are used by physicians to collect and document clinical encounters with patients and thus creating digital health records of patients during one or more patient visits (Zhang et al., 2011). The generated data is useful for a wide variety of purposes (Van der Lei, Moorman, and Musen, 1999) and their use has enhanced clinical practice, resulting in detailed access to patient information with the potential to improve healthcare (Edinger et al., 2018).

Traditionally, doctors have always collected data related to their patients during encounters with patients and this information was recorded on paper and kept securely in a cabinet (Obotu, 2018). However, studies have claimed that paper based records cannot support efficient patient care (Wigertz, 2001). In addition, the information overload of general and patient specific information which was evident by the bulging files of patients especially for patients with chronic diseases magnifies the challenges of maintaining traditional paper records (Liaw, Radford and Maddocks, 1998) and are now been recognized as inadequate in addressing the needs of modern medicine (Shortliffe and Cimino, 2014).

In the recent past, the adoption of electronic health records in documenting and managing health records (Roberts, 2017), (Evans, 2016; Zhang and Elhadad, 2013) has been on the rise. Its advantages include improving the completeness of clinical documentation and support of clinical decision making (Tang et al., 1999). It also improves clinicians' information retrieval from patient clinical narratives (Tange et al., 1998).

Hence, in many modern healthcare delivery settings, medical practitioners document all patient related information using electronic health records (Bates, 2005) resulting in availability of clinical documents in electronic form. Health records that used to be hand-written on paper are increasingly available in digital form (Boonstra, Versluis and Vos, 2014), (Hsiao and Hing, 2014) offering opportunities for automated computational tools to be leveraged to extract information from clinical texts (Carrell et al., 2014) hence improving healthcare delivery process. It has created opportunities for the reuse of generated data using automated search and analysis (Roberts, 2017) which was not possible with paper records. A good example is building prediction models using longitudinal electronic health record which can accelerate personalized medicine which in turn informs better clinical decisions (AlSaad et al., 2019). In addition, the EHR data can be used by clinical researchers to design quantitative models that can help in understanding the information contained in EHRs (Ruan et al., 2019).

1.2.3 Clinical documentation frameworks and medical ontologies

Despite the fact that most clinical records are free narrative texts, they are frequently organized into sections. When physicians write clinical notes, they usually split their narratives into general categories using conceptual or electronic templates (Tepper et al., 2012). Typically, doctors record their encounters with their patients in accordance with established documentation standards such as POMR (Problem Oriented Medical Record) (Salmon et al., 1996), APSO (Assessment, Plan, Subjective, Objective) (Sieja et al., 2017), SOAP (Subjective, Objective, Assessment, Plan) (Reznich, Wagner and Noel, 2010), APIE (Assessment, Plan, Implementation, and Evaluation) (Häyrinen, Saranto and Nykänen., 2008) which helps in providing documentation structure and hence helping doctors to quickly understand patients' medical charts (Reznich, Wagner and Noel, 2010), (Edinger et al, 2017). The SOAP documentation format is used to organize clinical notes to facilitate decision making, reasoning, and evaluation. It is a commonly used documentation format for healthcare providers (Lew and Ghassemzadeh, 2019), a problem-solving documentation technique that allows physicians to identify the patient's health concerns. It organizes clinical information into four sections; Subjective, Objective, Assessment and Plan. It is typically used in primary health care settings, and therefore clinical notes narrating clinical encounters recorded during patient visits are often written using SOAP notes (Judd et al., 2018). Information about a patient is written or presented in a SOAP note in a specified order and with a specific section for each facet of information. Many hospitals use electronic medical records, which are frequently populated with templates that insert information in the SOAP note format. These clinical notes are written in the SOAP format, with each section represented by a section heading that corresponds to one of the four categories within the SOAP structure (Ganesan and Subotin, 2014). The SOAP structure provides a consistent format for organizing patient information, that is useful when reviewing a patient's chart. Clinical documentation consists of narrative text that contains information about a patient's encounter with a physician (Sondhi et al., 2012). These are classified into four SOAP sections: subjective, objective, assessment, and plan, each with a different type of patient information (Cresswell, 2016).

i. Subjective: Details about a patient's condition written in patient's own words It also includes information such as social history, family history, current medications, and so on.
ii. Objective: Observable data such as physical examination findings, test results, vital signs, age, height, weight, and so on.
iii. Assessment: A listing of possible diagnoses
iv. Plan: Information on the patient's next steps of action, such as a treatment plan

S: Patient reports not much sleep last night; no complaints this morning.
O: T 99 F, HR 68, RR 16, BP 107/75
Chest – CTA, bilateral breath sounds
CV – RRR without murmur
A: Ovarian carcinoma – POD #1 for staging laparotomy. Adequate UOP, incision in good condition.
P: Clear liquids today. D/C foley catheter.

Figure 1.1: Sample SOAP Format (Adapted from (Edinger et al, 2017)

Medical ontologies such as HL7 CDA (Dolin et al., 2006) are also used to standardize clinical narrative texts. However, they are still in their infancy stage and have not yet been implemented in clinical practice. In addition, they do not include metadata needed for efficient information retrieval (Spat et al., 2008). However, creating medical ontologies is expensive and time consuming task (Trivedi et al, 2018), (Trivedi, 2015). In addition, ontologies rely on domain knowledge that is extremely expensive and difficult to capture and formalize (Musen, Shahar, and Shortliffe, 2006).

1.2.4 Data-driven Healthcare

In the last few years, healthcare industry has become a data driven industry. The continued growth of data being generated is colossal and the main focus has shifted from trying to produce medical data to trying to analysing it (Ross, Wei and Ohno-Machado, 2014). Currently, there are three obstacles impeding the use of electronic health data; patient privacy and security concerns; the fragmented and incompatible nature of the variety of EHR platforms used today; and the unstructured nature of the majority of the clinical data (Murdoch and Detsky, 2013). Before treating a patient in a healthcare setting, a medical practitioner is required to review a patient's clinical history. This entails reading through a medical record of a patient at hand. With the increased use of electronic health records, these records are now available in electronic form, removing the need to sift through a stack of papers to find information (Aggarwal, Garhwal and Kumar, 2018). Furthermore, such data availability is a rich source of medical data for medical research; however, the unstructured nature of clinical narrative texts makes computational analysis difficult (Aggarwal, Garhwal and Kumar, 2018). Therefore, clinical data generated by electronic health records in most cases remains underutilized resource (Jensen et al., 2012), (Henriksson, 2013), which, if tapped, has potential to improve health care (Rajkomar et al., 2018), (Henriksson, 2013) and medical research (Jensen et al., 2012). Analysing clinical data is a demanding task; because the majority of clinical data is in narrative form (Kong, 2019), (Henriksson, 2013), (Hicks, 2003) expressed in a natural language requiring one to read through. This therefore requires NLP techniques to handle narrative texts (Henriksson, 2013). The development of NLP algorithms to automate the processing of clinical texts into a form that can guide clinical decisions is critical to unlocking the full potential of EHR data (Sheikhalishahi et al., 2019). Clinical narrative texts provide vital patient information, however it is difficult to process them using computational tools since they lack a predefined data model (Ruan et al., 2018). Unstructured clinical narrative texts contain very informative information but because it is challenging to process using computational methods (Roberts, 2017); much of this information remains underutilised (Henriksson, 2013). Important clinical information is captured in unstructured textual documents. Techniques for supporting information extraction and retrieval are currently lacking. Data visualizations and other data analytics techniques could help both healthcare professionals and researchers find the information they need. For example, a visualization system that visually displays only important information in a clinical document would help the doctor save time by eliminating the need to manually read hundreds or thousands of medical histories within a short time period. Furthermore, it can help in analysing of detail medical record of each patient by showing medical progression over time. Tools that can provide succinct summaries of patients' medical histories are particularly very useful. Medical record summaries (Mønsted, 2015) have been used to provide physicians with good cognitive support by guiding the reading of the medical record and facilitating communication and collaboration between different clinical teams.

Traditionally, visualization (Card, Mackinlay and Shneiderman, 2007) has been used to amplify cognition of data analysis experts. Research such as (Gotz and Borland, 2016), (Hammond, West and Borland, 2015) shows the potential of visualizing health data to support doctors analyse and understand data during care episodes.

Research shows that doctors suffer from cognitive overload due to the large number of electronic patient records (Koopman et al., 2015). Because most of this information is available in narrative free text, clinical documents are frequently lengthy, with data redundancy issues that make it difficult for physicians to navigate and compile information during time-constrained patient care (Huang et al., 2018), (Wrenn et al., 2010), (Beasly et al., 2011), and (Zhang et al., 2011). According to research, physicians are suffering from cognitive overload as a result of unprecedented volumes of electronic clinical documentation (Koopman et al., 2015). According to (Farri et al, 2012), "EHR clinical document synthesis by clinicians may be time-consuming and error-prone due to the complex organization of narratives". For instance, the lengthy and redundant nature of the document may compromise legibility and increase time required to review the note (Payne et al., 2010). Users leveraging electronic health data for secondary purposes also encounter the same challenges when searching for information in clinical texts (Edinger et al., 2017).

Electronic health records have opened up opportunities to improve patient care and facilitate clinical research (Ruan et al., 2019) due to the availability of detailed clinical records that can be used to improve health care and clinical research. However, utilizing the available information to achieve this is not easy. The rapid growth of clinical information means that huge amounts of information are becoming immediately available and readily accessible and this unprecedented availability of large amount of clinical information with no support for analysis is a problem physicians and clinical researchers face (Wang et al., 2010), (Wang et al., 2011). Physicians may be unable to provide quality healthcare in the absence of this comprehensive, easily accessible information. Furthermore, if there is too much information in a time-constrained situation, the impact on physician performance is magnified. Humans have cognitive and perceptual constraints, according to Chittaro (2001), that limit the quantity of information a user can review and manipulate at any given time. There has always been documentation of unstructured free text health records (Chu and Cesnik, 2001), (Segev, Leshno, and Zviran (Segev, Leshno, and Zviran, 2007). As a result, medical records are difficult for machines to analyse and process (Segev, Leshno and Zviran, 2007). This means that users will not be able to utilize the increasingly large amounts of clinical data due to availability of too much information. Given the growing volumes of clinical data in electronic health record systems, text summarization, in which relevant patient information is summarized by a software application and presented to the user, is extremely useful (EHRs). The primary goal of a summary is to reduce the size and content of a text document to the essential points. This results in information simplification, with only the most important and relevant information from the document presented. As a result, using clinical datasets from electronic health records for patient care and clinical research has become the norm in the twenty-first century (Liu et al., 2019). Clinical datasets generated during clinical practice enable physicians to use them at the point of care, as well as medical researchers and data analysts to conduct clinical research and data analytics to support better informed clinical decision-making and evidence-based medicine (Liu et al., 2019), (Cohen and Elhadad, 2013). (Zhang et al., 2011).

According to (Meyer*,* 2019), the rapid growth of healthcare data in recent years has necessitated the need to present this data in ways that are more understandable and insightful (Meyer, 2019). Data visualization and particularly text visualization is an emerging data analytic field which attempts to achieve this objective. From the literature, there are various research works on text visualization of clinical text documents which has shown great potential to support a wide range of medical and healthcare functions such as health records review and clinical decision support. However, like in many other health data analytics techniques, preserving patient privacy while visualizing data is still a challenge. Privacy-preserving data visualization is a nascent research area that is emerging in response to success in visualizing electronic health records. Research works such as (Farri et al., 2012) has demonstrated that visualizing clinical documents is useful in aiding clinicians overcome the challenge of information overload occasioned by too much clinical information in electronic health records. Text visualization techniques are becoming increasingly valuable in summarizing clinical notes, though few applications have been integrated into health care systems to date. According to Ona and Sedig (2016), existing health data visualization tools use simple charts like bar charts and scatter plots that only represent a few facets of data and thus support perceptual and cognitive tasks. However, such tools may be ineffective when dealing with tasks that necessitate the investigation of various aspects and elements of big data (Ola and Sedig, 2016). Visual analytic systems, according to Cook and Thomas (2018), enable users to interactively explore and derive insights from massive amounts of data by leveraging human visual perception and abstract reasoning. There are also many active research works reported in the literature on using text visualization to tackle the aforementioned problem. Health data visualization application targets both electronic health data for individual patient (Popow, Unterasinger and Horn, 2001) and patients' aggregate study of several temporal trends in diagnosis, treatments and patient plans (Popow, Unterasinger and Horn, 2001) for clinical research. While text visualization offers great potential in enhancing physicians' abilities to review patients' clinical documents and researchers' abilities to evaluate large datasets, also presents new challenges in preserving the privacy of patients. Text visualization of electronic health records has the potential to improve care and clinical research, but also create the risk of disclosure of patient identifying information, raising confidentiality and privacy concerns. Visualization of electronic health data is an innovative and creative way of analysing and using the ever-increasing volume of clinical data generated during patient care. Visualizing information and knowledge hidden in textual documents is becoming an increasingly important research area in the field of data analytics but it relies on different algorithms to structure text and make it amenable to visualization (Sultanum et al., 2018). There is need of a model which structures narrative text documents by classifying them into multiple predefined information facets and providing a way of viewing these classified medical classes from narrative text in electronic health records. It organizes and presents classes of relevant clinical information without overwhelming them with extraneous information.

1.2.4.1 Utility of Electronic health records

The health record of a patient is important source of important information. It provides the physician with precise health data to help in formulating an accurate diagnosis, planning an appropriate treatment, and monitoring patient's medical progression. Elicitation of patient's complaint is one of the basic tasks of physicians in any patient encounter. Information such as major complaints, health concerns, symptoms etc. should be recorded for each medical encounter. The info in a patient's medical chart is useful for clinical care and research. To achieve the utility of electronic health records, demands appropriate computational tools to help in analysis and presentation of information.

In the research community, clinical data has been recognized as having great potential for improving care efficiencies, informing clinical decision making and clinical research (Ryan et al, 2017). Promising research examples include Korytkowski et al (2016) who developed a methodology for identifying prevalent and incident cardiovascular disease using clinical record. Traditionally, patient data is used to support direct patient care (Karlsson, 2010) and with the availability of digital records, has also led to the emergence of secondary purposes such as data mining (Karlsson, 2010), (Taranu, 2016), (Huang, Juarez and Li, 2017) ; big data analytics (Raghupathi and Raghupathi, 2014), (Reddy and Sun, 2013); Natural language processing (Velupillai et al., 2015), (Chapman, 2010), (Velupillai et al, 2015); clinical text analysis (Sakr and Elgammal, 2016), (Chute et al, 2010) and data visualization (Gotz and Wongsuphasawat, 2011), (Monroe et al, 2013), (Popow, Unterasinger and Horn, 2001), (Harris and Henderson, 2016).

With the increasingly use of EHR worldwide, there is a growing demand to extend the use of EHR data to support clinical research (Liu, Weng and Yu, 2012), (Coorevits et al, 2013), (Institute of Medicine (U. S.) and Grossmann, 2010), (Casey et al, 2016). However, this is being hampered by the fact that much of this data is in narrative text form (Roberts, 2017), (Sjoding and Liu, 2016) which is difficult to query and also not easily processed by computers (Roberts, 2017), (Henriksson, 2013). Whereas human beings can easily identify related concepts and create meaning out of written text, it is challenging for a computer to understand the unstructured text popularly used in clinical documentation. The unstructured narrative text has a detailed information (Zhou et al., 2006) about patients' medical histories and treatments, their trajectories of illness and recovery, and their clinical outcomes which is important information for contextualizing and improving patient health (Sjoding and Liu, 2016). It typically reflects the doctor's assessment of the patient's condition, prognosis, and response to therapeutic interventions (Raghavan et al., 2014). As a result, valuable information remains locked in clinical narrative texts, and although human readable, they pose a major barrier to computational analysis. Physicians and researchers need to explore these large volumes of clinical information to efficiently gain data insights as fast as possible. However, the unstructured nature of clinical documentation limits physicians from quickly finding desired information given the large volume of texts that needs to be read (Ruan et al., 2018). Therefore, there pressing need of software tools that can help clinicians (Marchesin, 2018) and researchers (Cole et al., 2016) to make clinical decisions from the available clinical data. The use of electronic health records in healthcare delivery have greatly increased availability of clinical documents and benefited healthcare management and research (Li and Qin, 2013). The digitization process has significantly improved the access to these clinical documents while ensuring their continuous availability; however, to make them easy to search and locate information is still challenging. To support patient care and secondary purposes require the ability to find desired information with a high degree of accuracy in electronic health data (Edinger et al., 2018).

They provide a vast amount of digitized patient information ranging from collections of clinical notes to discharge summaries and provide useful patient information. Physicians navigate this to satisfy various information needs.

1.2.4.2 Clinical narrative text

In medical practice, narrative text is mostly used to document patient care episodes which produce a number of clinical textual records. Narrative text which is also called unstructured text is still the most prevalent medium for communicating and sharing information (Hughes et al, 2017). Unlike structured data, narrative text provides detailed information about a patient medical history, such as symptoms, diagnosis, and disease of the patient. Natural language in narrative text form is used to document clinical information obtained during clinical encounters with patients (Roberts, 2017), (Kaurova, Alexandrov & Blanco, 2011).

Table 1.1 Sample structured data

Date	Diagnosis	Provider	Location
Apr 8, 2017	hepatitis	Super User	Outpatient Clinic
May 2, 2017	Cough	Super User	Outpatient Clinic

> ILLNESS : The patient is a 47 year old male , with end stage liver disease secondary to hepatitis C cirrhosis diagnosed about 5 years prior to admission .The patient had undergone treatment with interferon and Ribavirin .He had been admitted to the St. Margaret 's Center for Women & Infants multiple times early in 2013 for management of encephalopathy and ascites .The patient had been discharged from the St. Margaret 's Center for Women & Infants on 2013-05-06 , but was readmitted on 2013-05-09 when noted to have worsening renal function .The patient 's serum creatinine on the day of discharge , on 2013-05-06 , was 1.9 , but was noted to increase to 3.2 on 2013-05-08 , and was further elevated to 3.6 on 2013-05-09 .The patient was admitted with concern for hepatorenal

Figure 1.2: Sample unstructured data

In contrast to structured data, unstructured data are in free narrative text form, which makes it difficult for computer methods to analyse and get useful information. Narrative texts are not as easy to categorize as structured data. Clinical information, e.g. patient symptoms obtained during a patient's visit, is often recorded as narrative text. A doctor's letter pointing out medical symptoms would have to be read and interpreted by humans due to natural language texts.

In health domain a number of clinical documents like clinical notes, progress notes, discharge summaries etc. are documented using narrative text which presents computational analytical challenges (Roberts, 2017). On the other hand, clinical documents preserve a large part of their knowledge in narrative text form (Sultanum et al., 2018). Notes are mostly used in recording information about the health history of a patient (Hughes, Kotoulas and Suzumura, 2017) because of its expressive and flexible nature (Sultanum et al, 2018). In addition, narrative text is preferred because it is memorable and expressive and can therefore be used to easily document patient encounters (Loudon, 1993). Narrative text remains the reference for accurately describing medical knowledge (Lamy, 2017). It is therefore the preferred means of documentation for physicians (Rosenbloom et al., 2011) because it is convenient to express concepts and events using a natural language. However, it is difficult to search, summarize or support decision-support and statistical analysis (Meystre et al., 2008) in narrative text documents. The lack of structure in narrative texts makes it difficult for a doctor to manually study the contents of clinical documents and gets worse as the length of the documents increases. Gaining knowledge from this can be difficult and time-consuming due to its unstructured nature (Shneiderman, Plaisant and Hesse, 2013).

The content of clinical text documents contains important information necessary to understand the medical profile of patients (Bossen and Jensen, 2014), and this is where doctors take time reviewing a patient record (Reichert et al., 2010) by scanning through clinical notes with a view of identifying key problems and getting an overall impression of the status of the patient (Hughes et al, 2017). However, these documents lack consistent structure and content (Uzuner et al, 2010). It is very useful to produce summaries of clinical text by providing a condensed and efficient view of clinical information relevant to the patient. It is also important for physicians to have complete and accurate health history of patients in chronological order (Jung, 2011). Although, various types of clinical records (e.g., discharge summaries, consultation notes, etc.) contain comprehensive medical history information, it is always challenging and time-consuming to read and comprehend the medical histories of patients when information is stored in multiple documents in different formats and the relationships among various pieces of information is not explicit. Reviewing patients' historical health information during care episodes requires time critical decision-making based on different clinical documents written using narrative text. Physicians use electronic health records for time-limited patient interactions that require the synthesis of large amounts of clinical text (Farri et al., 2012). Due to time constraints in medical practice, use of clinical textual documents presents a number of challenges:

i. Long clinical documents such as records of patients with long medical cases become time-consuming to peruse which makes it challenging for physicians to obtain useful information within a short time period. It is therefore a challenge for doctors to gain an overview of the patient medical history (Shneiderman, Plaisant and Hesse, 2013).
ii. Computability challenge which is the difficulty of using unstructured text utilizing automation tools that can help a physician to obtain a review of a patient's health history in a patient medical chart (Christensen and Grimsmo, 2008), (Jensen and Bossen, 2016).

A patient health record is made up of many reports, created during a patient visit to hospital (McKeown, Elhadad and Hatzivassiloglou, 2018) and can be viewed as a sequence of treatment instances, and each instance is documented on a patient medical chart (Sorgente et al., 2013). A patient's clinical details are noted by the attending physician on a patient medical chart. This makes the medial chart a source of clinically relevant patient information. However, it consumes a lot of time for humans to read these notes and establish the best course of action for the patient. When using electronic health records (EHRs), physicians need to display a patient record on the computer screen to identify important patient information. Searching for information can be overwhelming when physicians try to find answers to general questions; they often are faced with a daunting amount of text documents.

A patient's medical record is usually made up of a number of documents, including clinical notes, discharge summaries, letters, medical text charts and so on. Physicians are required to read, understand and summarize this earlier documentation for the patient at hand (Kvist et al., 2011), however, they usually don't have enough time to read them carefully (Scott, Haller and Fettiplace, 2019). These clinical documents contain important information needed to understand a patient's medical status. However, retrieving and using the information in clinical textual documents during clinical review is difficult and time-consuming which can negatively affect the review and comprehension of patients' medical histories. Retrieval of information from clinical documents for clinical review worsens as records grow longer and time pressures increase (Sultanum et al., 2018). Long clinical documents can be encountered for example with patients associated with chronic conditions (Bashyam et al, 2009). This situation introduces a new problem, the difficulty of quickly obtaining a comprehensive review of a patient's health history from large collections of documents without manually going through the details of each sentence. Time constraints for patient encounter can be experienced where physicians have a limited time for each patient (Scott, Hallett and Fettiplace, 2013) due to many patients, such as in resource limited countries where the doctor to patient ratio is high (WHO, 2016). In both cases, the task of looking for information pertinent to a subject of interest is impaired which limits the detail of overview physicians can get. As the adoption of electronic health records increases, increasing amounts of documents can overwhelm doctors, creating cognitive challenges for doctors reading and using these documents (Ferri et al., 2012). Current electronic health records (EHRs) have been associated with excess cognitive workload (Mazur et al., 2019) and their usability continues to be a major concern among the physicians (Ratwani et al., 2015a), (Middleton et al., 2013) due to usability challenges such as user interfaces with confusing layouts and containing too much or too little relevant information as well as workflows and alerts that are burdensome. These challenges have been cited as contributing to physician burnout (Howe et al., 2018), (Shanafelt, Dyrbye and West, 2017). Similar challenges are experienced by those performing population studies over large collections of historical health data. Although the medical informatics community has sought to develop systems that can assist physicians in their day-to-day clinical practice by providing information, very few of these systems have been adopted and most physicians continue to practice without them (Smith, 1996). These documents are documented with narrative text in which the order of the words follows grammatical rules (syntax) and the meaning of the text can be interpreted by a human reader (semantics). Much of the information usually comes from written text or from dictation transcribed text, or even from the use of speech recognition applications (Meyestre et al., 2008). Given the challenges associated with physicians reviewing and analyzing clinical documents, assisting in the rapid synthesis, interpretation, and presentation of clinical information is becoming an important research challenge. It is important for physicians to easily understand complete medical histories of patients which may include disease/symptom progression over time and related tests/treatments in chronological order. Although, clinical documentation has comprehensive medical histories of patients, it is always challenging and time-consuming to comprehend the histories of patients when patient medical histories are long and when there is less time to manually review the clinical documentation. The value proposition of electronic health records can only be realized once the data has been summarized and the meaning of the data has been determined. Current health information systems do not have tools for summarizing patient records in a way that allows for clinical review and cognitive reasoning (Pivovarov and Elhadad, 2015). As a result, doctors must manually search clinical documents for current and relevant information (Ayatollahi, Mirani and Haghani, 2014). Information presented in symbolic form can be processed cognitively more efficiently than information presented in its raw form (Workman, Lesser and Kim, 2007).

1.2.4.3 Information overload problem in healthcare

In medical practice, doctors usually review patients' medical histories by looking at important medical concepts from a clinical document such as a patient medical text chart. Retrieving and analysing patient's clinical data is important for assessing the patient health history. However, it is challenging to retrieve information from medical text (Hanauer et al., 2015) as it is time-consuming to read the entire document especially for long medical histories. During patient encounters, a physician needs to get an overview of a patient's past clinical history to put the patient's complaints into context (Devarakonda and Mehta, 2016). Currently, the review process of electronic clinical documents is a time-consuming activity and a single patient clinical document may take a substantial amount of time to be reviewed during consultation. Current health information systems such as electronic medical systems store a substantial amount of unstructured narrative texts. Presenting narrative texts in their raw form prevents doctors from immediately finding required information due to the large amount of text that must be read (Ruan et al., 2018). When a physician is treating a specific patient, he or she is looking for information relevant to the patient's history and problems.

It takes a lot of work to read narrative texts to locate the relevant ones. It is getting harder and harder for manually reading to keep up with the rate of information growth. Finding, extracting and summarizing important concepts or phrases from narrative texts (e.g. medical notes or a patient report) for further analysis is therefore a challenge. This is especially the case for clinical documentation in electronic health records (EHRs) where physicians perform documentation using electronic health record systems (EHRs) (Huang et al., 2018) and are able to record and maintain a large set of data with ease (Qiu, 2014). Understanding the holistic picture of the patient's medical history is critical to accurate treatments. Automatic techniques for summarizing text documents are crucial in today's healthcare setting where there is an over-abundance of clinical data and lack of personnel as well as time to interpret the data. Support is therefore essential to successfully utilize these electronic clinical documents to improve healthcare delivery and even clinical research by providing automatic analysis and discovery of relevant clinical information from large textual datasets. Therefore, there is a pressing need for automating analysis of patient's clinical records. To review and explore such data requires identification of important clinical concepts in a clinical document and displaying a concise summarized view to the physician. Such concise summaries can help doctors in reviewing patients' medical charts by enabling them to quickly review patient's medical history and making medical decisions that are useful in-patient care. For example, clinical notes contain important patient's health history, which may include a doctor's observations and documentation about their interactions with patients.

1.2.5 Challenges of digital health records in medical practice

In medical practice large amounts of health documentation about individual patient's care are produced by different actors. The prevalent use of electronic clinical documentation systems in healthcare delivery increasingly leads to three main problems:

i. Unstructured nature of clinical data - Clinical notes is the most common way of capturing patient clinical data and most clinical notes contain a lot of information scattered throughout the report without following a structure, which makes it a challenging task for physicians to identify and extract the relevant patient information during time constraint care episodes

ii. Key information retrieval problem- The problem of manually reviewing clinical documents (e.g. patient chart) which is laborious, particularly with patients having long clinical histories especially in our contemporary society where there is increase prevalence of chronic diseases with many hospitalizations and consultations (Kreuzthaler et al., 2018).

iii. The problem of information overload (Zeng-Treitler and Cimino, 2011), (Reichert et al, 2010), which affects all actors in the health system and threatens to hinder the use of electronic clinical data in medical practice and clinical research (Moen et al.) al, 2014). The information overload, combined with clinician time constraints and cognitive limitations, has outstripped people's ability to use electronic health records (Singh et al., 2013). Empirical studies have found out that, EHR data is cognitively taxing to navigate due to huge volumes, heterogeneous data and are chronological organization (Roman et al., 2017),(Christensen & Grimsmo, 2008).

For this reason, the extraction of important clinical information from clinical documents is a major problem in healthcare today, as physicians have at their disposal detailed patients 'clinical data (Moen et al., 2014), (Moen et al., 2015) but no computational tools to extract information. Therefore, we have a problem of growth of medical information without a matching advancement in information extraction tools. Information extraction is a useful task of machine learning and natural language processing which entails extracting meaningful pieces of knowledge from natural language text (Ghoulam, Barigou and Belalem, 2015) and it has shown promising results in extracting the embedded information in unstructured clinical texts (Liu et al., 2019). Jackson et al (2017) developed and validated a model which demonstrates the possibility of automatically extracting symptoms from discharge summaries.

Practicing doctors usually hold appointments with patients whose medical files contains patient clinical documentation with few to thousands of notes. Traditionally, the patient's file would have been in paper form commonly referred to as patient medical chart which sometimes were so large that multiple files were necessary. Nowadays paper records are being replaced by electronic records, but the general form and function of the medical record remains the same; physicians' write and read narrative notes (e.g., medical chart, discharge summaries, prescription notes etc.). According to Roberts (2017), the shift from paper health records to electronic health records, have created opportunities for reusing this clinical information through automated analytic techniques (Roberts, 2017), however this is yet to be realized (Jensen, Jensen and Brunak, 2012). Utilising this information holds great potential for improving healthcare delivery (Velupillai et al., 2014).

Information overload is an emerging problem in medical practice especially for physicians, who are often faced with large amounts of patient data in clinical text charts of patients, either in paper or electronic form. Typically, physicians have limited time to review and process clinical documents, and information overload can lead to errors. Secondly, depending on the clinical tasks, only relevant information may be of interest to physicians e.g., symptoms. Displaying only relevant information can be useful in reducing the problem of information load. The use of Health information systems in healthcare delivery has greatly increased availability of clinical data which has the potential to support healthcare management and research (Korytkowski et al, 2016). For example, clinicians can review previous clinical data such as medical tests, laboratory data etc. (Reichert et al., 2010). However, accessing relevant information embodied in this data is a time-consuming and inefficient process (Reichert et al., 2010). While electronic health records are very effective in documenting patients' medical histories, they lack the functionality to synthesize the available data for a given patient, especially when it comes to the information in narrative notes (Reichert et al., 2010). In particular, they lack cognitive support (Assis-Hassid et al., 2019), (Ratwani et al., 2015b) and there is lack of research that adequately addresses the need for visualization tools that can reduce cognitive strain during decision making (Faiola, Srinivas and Hillier, 2015).

A good example is an outpatient setting, where patients may have long clinical histories accumulated over several years, which is common with patients with chronic diseases (Weir and Nebeker, 2007). Therefore, the increased availability of electronic health data in healthcare has not led to increased accessibility of information (Hanauer et al., 2015). Most of this useful information remains embedded in clinical narratives (Van Vleck, 2010) which are tedious to read (Van Vleck, 2010) and time consuming (Reichert et al., 2010), (Popow, Unterasinger and Horn, 2001) within the context of a standard clinical encounter (Van Vleck, 2010) and may limits the physician's ability to get timely clinical information. In the recent past, this availability of large volumes of clinical text documents, has led to significant interest towards automating their processing and analyses (Hassanzadeh, Nguyen and Koopman, 2016) and there are many studies on how to process clinical notes and extract knowledge from them (Griffs et al, 2016). Van Vleck (2010), investigated how to identify relevant problems in patient clinical notes that may interest a physician seeing a new patient.

With the increase use of electronic health records in healthcare delivery, there is need for effective and efficient text visualization tools that can summarize clinical documents and aid physicians and researchers (Wang et al., 2011) to effectively and efficiently locate relevant information and therefore enhancing faster and easier comprehension of patients' clinical histories. Clinical documents can be described by a number of abstract concepts such as symptoms, diagnosis, disease or treatment. Machine learning (ML) models have been trained to automatically map sentences to these abstract concepts, allowing reviewing very large text collections, more than could be manually.

Applying data analytics techniques to large clinical documents generated and stored in electronic health records has shown great potential in supporting a wide range of medical and healthcare functions such as health records review and clinical decision support. Health data visualization is generally accepted to be useful in aiding clinicians overcome the challenge of information overload which has been occasioned due to the present of too much clinical information in electronic health records. According to Laxmisan et al (2012), the adoption of electronic health records (EHRs) has enhanced collection of large amounts of patient-specific health information over long periods of time which translates to a lot of detailed patient information (Yao, Mao and Luo, 2019) being made available, describing all aspects of patient's care in addition to being available to every clinician during every patient encounter (Laxmisan et al, 2012). As a result, the large volume of clinical records in form of narrative text is being generated progressively. However, the constantly growing volumes of health data makes it difficult to utilize this information due to availability of too much information. In computing, this has popularly become known as information overload problem. While information is getting richer with recording more and different kinds of patient attributes, using it to support patient care and research is becoming increasingly difficult. So, it is desired to develop an efficient and effective clinical document analysis system for analysing clinical documents. To help physicians cope with the ever-increasing amounts of text documents and utilize electronic healthcare information, demands the design of new computational tools that make patient data easily accessible and also present a summarized and organize view of information thus allowing physicians to navigate patients' medical records without having to peruse all the documentation in a patient medical history.

Applying, text visualization, in which relevant patient information is automatically identified by a software application and presented to the user in a visual format, is very useful given the growing volume of clinical data in EHRs. Visualizing clinical documents could help users to easily explore large amounts of unstructured text and get summarized views which can help physicians and researchers easily interpret patients' medical histories for better understanding of patients' health histories. Clear and organized summaries can help doctors to identify key information, facilitating understanding of a patient medical history and saving doctor's time by easy access to needed information during care episodes.

Visualizing a single patient record can support key clinical care activities such as providing an overview of patient history. From the literature, there are many clinical data visualization tools which have been developed and tested on a variety of clinical data. They are designed to be effective time-saving tools which provide doctors with a wealth of diagnostic information in clinical practice. This, in turn, will help physicians devote more time to patients during consultations by facilitating prompt decision-making for an individual patient, freeing up time to be spent with patients. Physicians will most likely easily digest and understand information faster from data that is presented visually than in textual form and help relieve physician's cognitive burden. Visual data is often easier to understand quickly than textual information and therefore this can enhance a doctor's core clinical duties. One central task in information visualization is displaying information in a context that makes it easier for users to understand. The primary objective of the proposed model is to reduce the time physicians spend reading long health documents to understand the patients' medical histories during consultations. The proposed model helps the physician to quickly get the structure of the document and the concepts and relations to read for a quick summary.

1.2.6 Information overload problem

The increasing problem of information overload in the digital age of healthcare is a serious issue which contributes to problems such as diagnostic errors, near misses, and patient safety, especially in critical care settings (Rand et al., 2018). This problem is mainly due to increasing use of electronic health records (Rand et al., 2018), (Clarke et al., 2013) that makes it difficult to find important information in large volumes of medical records and affecting physician's diagnostic thinking and efficiency (Zhang et al., 2010). A user looking for relevant information by searching information which may be hidden in a lifelong patient clinical record is a classical information overload problem.

Medical professionals are experiencing information overload problem due to increasing use of electronic health records (Clarke et al., 2017). With the explosion of information available to physicians in electronic health records, the health practioners faces information overload problems for many types of information. This makes it difficult to obtain important clinical information in clinical text documents, thereby seriously affecting a physician's work (Ruan et al., 2018). It is therefore challenging considering the limited time that physicians have to review and get the required information in a few minutes (Ruan et al., 2018). Therefore, there is increasing need to address this challenge of growing volumes of clinical information to support patient care and clinical research.

According to Sultanum (2018), physicians are under time constraints and usually meet patients for 15 minutes and likely have no more than 15 minutes between patients to review records. If a patient with a long medical history meets with one doctor and then another, research shows that it is improbable that both doctors will spend a lot of time reading over the full patient history (Sultanum, 2018). The application of visualization techniques to clinical data should help physicians to obtain comprehensive patient information efficiently than in the usual textual presentations (Ledesta et al., 2019). According to Weir and Nebeker (2007) information overload represents a significant obstacle to effective use of electronic health records in patient care. The amount of clinical information per patient may be too long, particularly for patients suffering from chronic illness and multiple morbidities (Bawden 2008; Reichert 2010; Duftschmid 2013). Reichert (2010) investigated the cognitive thought process of physicians during clinical document review process and showed that they spent more time reviewing clinical notes in order to identify problems, medical history, medications and so on.

From the literature, there are several empirical research studies which shows, that physicians encounter the problem of information overload when presented with large amount of patient clinical data in a time-constraint clinical setting (Mane et al, 2012). Complex medical cases for example lead to information overload, delays or missing information (Pivovarov, & Elhadad, 2015). A lot of available information means that human document review is time-consuming and labor intensive (Hripcsak, G et al, 2011), (Poissant, L et al, 2005). Despite the fact that; electronic health records provide access to large volumes of patient data; the ability of the human mind (Brooks, 2000) to process large amounts of data in real time situation is limited. Even though, data may be available in electronic form, access to specific information of interest is not readily available through automated means (Hanauer, 2006). Currently available commercial EHRs do not adequately meet this need and sometimes offer organization of data but not information synthesis (Laxmisan et al. 2012), (Badgeley et al., 2016). As electronic health systems continue to generate digitized healthcare data (West, Borland and Hammond, 2017), Many electronic clinical documents, which offer better access to information, are becoming more and more readily available, but also represent an additional cognitive burden for clinicians (Jabarek et al., 2018). There are currently still few tools which can help in synthesis and aggregation of medical data (Laxmisan et al., 2012). As mentioned before, research shows that healthcare domain suffers from the problem of information overload due to the unprecedented growth of digital health records (Pivovarov and Elhadad, 2015). One of the problems with large amounts of data, especially with unstructured text, is that it can often be difficult to digest quickly. Therefore, physicians and medical researchers need quick and efficient access to clinical information to make clinical decisions and research respectively. Therefore, there is need of an application that can make a visual representation of clinical text quickly, where a user can understand the text quickly.

1.3 Problem Statement

Clinical narrative texts contain a lot of information that requires automated techniques to lessen the cognitive load on doctors using electronic health records (EHRs). Narrative texts in transcription notes can be lengthy and, as a result reading can cognitively be tasking to a physician. Physicians have access to enormous amounts of clinical information in the form of narrative texts. Instead of exploring the whole information space, it is more feasible for physicians to look for information by browsing through information facets. Segmenting narrative text into multiple information facets makes the narrative texts more readable. In this section we state the problem associated with the use of digital clinical narrative texts.

1.3.1 Statement of the problem

The sections above have described several problems encountered in using clinical narrative texts in electronic health records (EHRs). One notable challenge is the difficulty of retrieving content from clinical narratives. In order to highlight the work to be addressed in this thesis, we defined a high level and more succinct problem description as follows: How can we support information retrieval from clinical narrative texts which are abundant in electronic health records to reduce physician cognitive load and support clinical decision making in a healthcare delivery setting?

Physicians face cognitive overload daily due to clinical narrative texts in electronic health record documentation. Retrieving information from these clinical narrative texts entails finding relevant patient-related information in a collection of clinical notes to support decision making. However, applying traditional information retrieval techniques is time consuming for large text collections. Therefore, finding patient-related information for use in making medical decisions requires a significant amount of time from doctors. The rapid increase of clinical health data poses a significant challenge for physicians, who use electronic health records in medical practice. Thus, the need for information retrieval support techniques that can retrieve relevant medical information in a patient clinical history has emerged. To address this challenge, and improve presentation of retrieved information both in terms of accuracy and ease of access of retrieved information, this thesis proposes a technique based on text classification and visualization to support information retrieval from clinical narrative texts. The proposed approach combines text classification and visualization to generate a visual map of information facets in a given clinical document. In healthcare, such technique can generate visual facets of information to save healthcare experts' time when browsing through the clinical history of a patient, especially in scenarios where the patient clinical information can be supported by patient past clinical record at the point of care. In this thesis we focus on the problem of focusing on the most relevant information in a potentially long clinical narrative text document. We envisioned technique to support information retrieval from clinical narrative texts. Our goal originated from a clinical requirement to reduce cognitive overload

1.3.2 Mathematical formulation of the problem

In this thesis we considered the problem of retrieving clusters of information in a narrative clinical text document using text classification and visualization with the objective of supporting retrieval of relevant information from clinical narrative texts.

We start with a formal definition of our problem as follows. We have a document D= $\{S, C\}$ made up of N consecutive sentences $S = \{s_{1,} \dots \dots \dots s_n\}$ and a set of information classes $C = \{C_{1,} \dots \dots \dots C_n\}$ as input. In our case, D is a plain clinical text document (e.g., patient medical chart). For each sentence $\{s_i\}$ in the document, there are distributions of C_n facets (classes) of information represented in this document.

Given a clinical document D, our task is to retrieve from document D a set of distinct facets (classes) of information $C = \{C_{1,} C_2 \dots \dots \dots C_n\}$, so that each retrieved information class $C = \{S_{i,} c_i\}$ contains a sequence of coherent sentences Sj ⊆ S and a class label yj that gives descriptive name to a group of these sentences (class). For a patient clinical chart, the sequence of class labels is $C = \{\text{Subjective}, \text{Objective}, \text{Assesment}, \text{Plan}\}$ and personal identifying information. In this thesis we tackled the problem by classifying and visualizing medical sentences in plain text clinical documents using deep learning algorithm.

Let $S = \{s_{1,} \dots \dots \dots s_n\}$ be a set of clinical sentences and $C = \{c_i | i = 1,2, \dots, |C|\}$ be the set of information classes (e.g., Subjective, Objective etc.). The task is to find a function $h : s_j \rightarrow c_i$ where i and j are integers in the range of, $1 \leq j \leq n$ and $1 \leq i \leq 5$ respectively.

This problem is a multi-class text classification problem. In this work, we used a convolutional neural network for classifying sentences into SOAP classes. Convolutional neural network is one of the state of the art classification algorithms.

After classification we visualize classified sentences using cluster map concept with the objective of presenting a structured organized clinical narrative texts thus overcoming the problem of information overload which is an acute problem especially in long narrative texts. Our approach presents a readable text structure and guides physician through the text by arranging a document into coherent information classes. To the best of our knowledge, the joined task of classification and visualization of multiple information facets of a document has not been done before. Cluster map maps for clinical narrative text, is demonstrated in this work. The inherent relationships in the information classes are shown by their arcs in the map. An obvious advantage of the cluster map is that it can be displayed on a screen. This makes it possible to support retrieval of information from the underlying narrative text, the cluster map will allow for efficient browsing and selecting of relevant information from the underlying text document space.

1.3.3 Justification

The growth of electronic health records in size and complexity poses users with greater need to have computational tools to help analyse and synthesize a number of clinical documents which are often maintained as unstructured text and constitute a large volume of clinical data. Reading long text documents can easily overwhelm users. The idea of semantic mapping, or grouping information into meaningful semantic clusters, can help the reader to get some order and structure of information embedded in a given document thus helping a user quickly get information from a possibly long document.

The proposed model is expected to ease presentation and search for key information in electronic clinical documents by providing an easier way of extracting and presenting the required information. During encounters with patients, doctors usually hold consultation sessions with their patient which entails a physician spending time familiarizing himself/herself with the patient's health history (Scott, Hallett & Fettiplace, 2013) which has patient information on previous medical encounter (Donaldson and Lohr, 1994).

This means, the more the time spends reviewing a patient medical chart, the less time spend interacting with the patient (Scott, Hallett & Fettiplace, 2013), (Howie et al, 1999). Previous research has shown that the quality of treatment outcomes increases as doctors spend more time with patients, examining their symptoms, understanding their conditions, and developing appropriate treatment plans (Royal College of General Practitioners, 2000). For instance, physicians use a patient medical chart to monitor the progression of a patient's condition. Clinical sentences and expressions in a patient medical chart document are usually short clinical notes written by doctors during care episodes which are fundamental to understanding the health history of a given patient during subsequent visits. The classification of these sentences and expressions into different semantic classes and their mapping in a cluster map representation with predefined reference clusters offers both an improved representation of salient clinical information in a clinical patient document as well as a common frame of reference to facilitate the information search and the argumentation in relation to a particular patient. Classification process maps raw sentences and expressions to specified semantic classes. Clinical sentences classified in the patient medical text chart are mapped to predefined semantic classes and then mapped to corresponding clusters in the cluster map. Clusters of semantically similar sentences appear together in one cluster node thus allowing interactive visual view by users.

1.4 Research Objectives

In this section we present the study's overall research objective and its specific objectives.

1.4.1 Overall research objective

The goal of this thesis is to develop an artefact that structure and organizes a clinical narrative text document into visual information facets of interest, providing a dynamic account of a patient's clinical history. The purpose of the artefact is to retrieve clinical information relevant for answering clinical questions about a patient case at hand.

1.4.2 Specific Research Objectives

In this research the specific objectives are as follows:

i. RO1: To investigate the challenges that physicians face in using clinical narrative texts in electronic health records (EHRs).
ii. RO2: To investigate different types of clinical information we can infer in a corpus of clinical notes and how to model them into information facets with their inherent relationships.
iii. RO3: To design and implement classification and visualization artefact to support information retrieval from clinical narrative texts.
iv. RO4: To evaluate the proposed artefact's classification model performance against other deep learning baseline models.
v. RO5: To evaluate how well the artefact solves the stated problem and meet the defined requirements

1.5 Research Questions

The common driving force behind this research was how clinical text classification and visualization can be leveraged to support information retrieval from clinical narrative texts. In considering the research problem a number of key research questions emerged, namely:

i. RQ1: What are the challenges physicians face in using clinical narrative texts in electronic health records (EHRs)

ii. RQ2: What are the different types of clinical information we can infer in a corpus of clinical notes and how can we model them into visual information facets with their inherent relationships?
iii. RQ3: How can we build an artefact that supports information retrieval from clinical narrative texts?
iv. RQ4: Which deep learning technique can build an artefact's classification model for effective clinical text classification?
v. RQ5: How well does the developed artefact solve the stated problem and meet the defined requirements?

1.6 Motivation

Currently the success of scanning through an electronic clinical document e.g., a patient clinical chart largely depends on an individual physician's ability to read a document and identify important concepts related to a patient health history; this success is largely anchored on an individual's ability to read, organize and relate simple facts. Many research works show that, physicians spend a significant amount of time reviewing and authoring clinical notes. As a result, many clinical notes may never be reviewed. Traditionally, these notes have been a rich source of detailed information about patients' medical histories and clinical care processes (Liang, Tsou, and Poddar, 2019). Therefore, the challenge is to provide physicians with efficient tools to retrieve and organize correct information to aid extracting information in long and sometimes fragmented clinical notes. Furthermore, a physician's efficiency and productivity are determined by their level of expertise in using computer systems. The proposed artefact is expected to standardize the process of scanning through a patient clinical chart or any other clinical document.

The patient data collected during care episodes potentially holds great value for patient care and clinical research (Denaxas and Morley, 2015), (Kleinberg & Elhadad, 2013). For research it can be used for large-scale longitudinal studies of a population (Kleinberg & Elhadad, 2013). Diagnosing a medical condition and treating it depends largely on the ability to identify the required medical information in such documents. One of the reasons why it is so important to quickly extract useful information from large amounts of information is patient care. Clinical decisions are usually made quickly, and it is important to review relevant medical information regarding a patient in order to make a well-informed decision.

Clinical decisions are usually made quickly, and in order to make an informed decision, it is necessary to review important medical information about a patient. The target audience for this research includes researchers and designers concerned about the problem of information overload in clinical settings, as well as clinical informatics researchers and practitioners looking for solutions and tools to support clinical practice and research.

1.7 Significance of the Study

The importance of this research lies in its emphasis on the practical classification and visualization of clinical narrative texts. Text classification and visualization can be used to support information retrieval from clinical narrative texts in electronic health records, and hence supporting physicians in decision making. The result of this research should fill fundamental knowledge gaps in our understanding of how clinicians use clinical documents in the context of their practice and can help future electronic health record user interface designers design visual interfaces that support the synthesis of clinical narrative texts and thus improve patient care. Our proposed technique is expected to provide clinicians an intuitive way of reviewing clinical narrative texts in electronic health records and ultimately improve patient care. Our objective here was to delve into the problem of how to assist a physician in quickly retrieving a specific facet or class of information in a clinical text document. The result of this research should be beneficial to several categories of entities. Specifically, the outcomes will:

i. Shed new light on the information overload problem posed by the generation of healthcare data.
ii. Shed new light to researchers on the development of privacy preserving models for visualization of electronic health documents.
iii. Act as an impetus and catalyst for further research on text classification and visualization of electronic clinical narrative texts.

1.7.1 Technical Significance

With the availability of digital clinical data, it is desirable to process it using automated systems to inform clinical decisions and enable secondary purposes such as research. To the best of our knowledge, our work is the first to propose the classification and visualization of electronic clinical data to create a visual map of a clinical document. We proposed a novel deep learning model, using a corpus of labelled to learn meaningful medical information in clinical narrative texts.

1.7.2 Clinical Relevance

With the increase use of electronic health records, huge amount of patient data including a number of clinical text documents, such as clinical notes are now available in electronic health records at the physicians' disposal. Physicians typically need to make clinical decisions by examining the wealth of data generated and made available by electronic health records. It contains useful information that can be used in patient care. However, because this data is unstructured, accessing relevant information is a time-consuming and inefficient process. This unstructured data is frequently written in natural language and contains critical information. Furthermore, the availability of clinical information in volumes greater than what can be read in the context of a standard clinical scenario is a significant challenge. In this thesis we have proposed a clinical document visualization model that succinctly captures all relevant information in a visual map thus helping physicians to locate important information during care episodes. The proposed model is a preliminary step toward the automated extraction of relevant clinical information from existing clinical documents and providing a visual summary of patient history. While we would not expect this model to replace humans, we anticipate that this study will influence the future development of clinical data visualization of electronic health records.

1.8 Scope

This research is limited to the classification and visualization of clinical textual documents and will only consider the techniques which could enhance usability in this context. Therefore, the other types of clinical data such as medical images are out of the scope of this thesis. The research will concentrate on text classification and visualization of patient clinical charts written using SOAP documentation format. The model concepts and design can later be replicated to other clinical documents.

1.9 Chapter summary

In this chapter, we introduced the concepts of electronic health records and *clinical narrative texts.* We identified the main problem faced by physicians in using clinical narrative texts in electronic health records. Access to health services in health delivery centers have been frustrated by the problems of overcrowding, long treatment time, delayed patient treatment, and high costs. These problems are due to several internal and external factors such as limited staffing and increased prevalence of chronic diseases (Sheikhalishahi et al., 2019), (WHO, 2014). In the last few decades, healthcare facilities have been experiencing an increasing number of patients seeking healthcare services. Such rising demands amidst limited resources leads to inefficiencies and long waiting times during care episodes. In addition, technology is increasingly playing a significant role in healthcare delivery processes. A classic example is the use of health information systems in healthcare delivery which has led to unprecedented amount of digital clinical documentation (Lesselroth and Pieczkiewicz, 2011) majorly in narrative text (Kong, 2019). Narrative text is always difficult to review by reading (Zhang et al., 2017) especially in cases such as emergencies (Ozturk et al, 2015) or patients with long medical histories (Vrieze et al, 2013). The use of electronic documentation is now becoming one of the biggest challenges in healthcare. Reviewing clinical documentation is a labor-intensive process, currently requiring a lot of time to read and interpret clinical text during healthcare episodes. The growing volume of clinical data in modern medical practice therefore creates difficulties for doctors when reviewing patients' medical histories in order to understand individual patients' medical histories. This has been confirmed by empirical studies such as by Young et al (2018) who found out that physicians spent more time using EHRs at the expense of patients during care episodes. As a result, doctors often have a fragmented view of the patient's history and may not deliver proper care. According to Pivovarov and Elhadad (2015), it is challenging for a physician to read hundreds of clinical notes during a patient regular medical visit.

An automated system for providing a complete, easy-to-review, visual summary of all the information related to a given patient would significantly help doctors during care episodes. Research to date on using machine learning and natural language processing has not yielded a satisfactory system. When reading a document, one can recognize sentences with some common semantic features, which can be grouped into distinct semantic classes i.e., grouping sentences under the same semantic class. The narrative text is presented by abstracting the sentences into group structures. A patient medical chart may contain various clinical sentences and expressions which may describe symptoms, diagnosis disease/condition or treatment. Classification of clinical documents into semantically classes and displaying them using a cluster map can be very helpful. Cluster map visualization technique can help communicates the most important information that are relevant to a patient. This can be used in patient charts to give doctors a quick, at-a-glance understanding of a patient's medical history. The cluster map displays information from past history and makes key information more visible and thus guides the doctor in reviewing the patient medical history. This visual tool could also guide the doctor to look further into the patient history by following various semantic classes or exploring minute details.

1.10 Thesis organization

The rest of the thesis is organized as follows: Chapter two discusses the literature review; chapter three discusses research methodologies followed. Chapter four presents the design and development of the artefact which is the solution to the problem identified in chapter one. Chapter five presents the results and discussion, followed by the Conclusion and contributions in chapter six. The organization of this thesis is shown in the diagram below Figure 1.3.

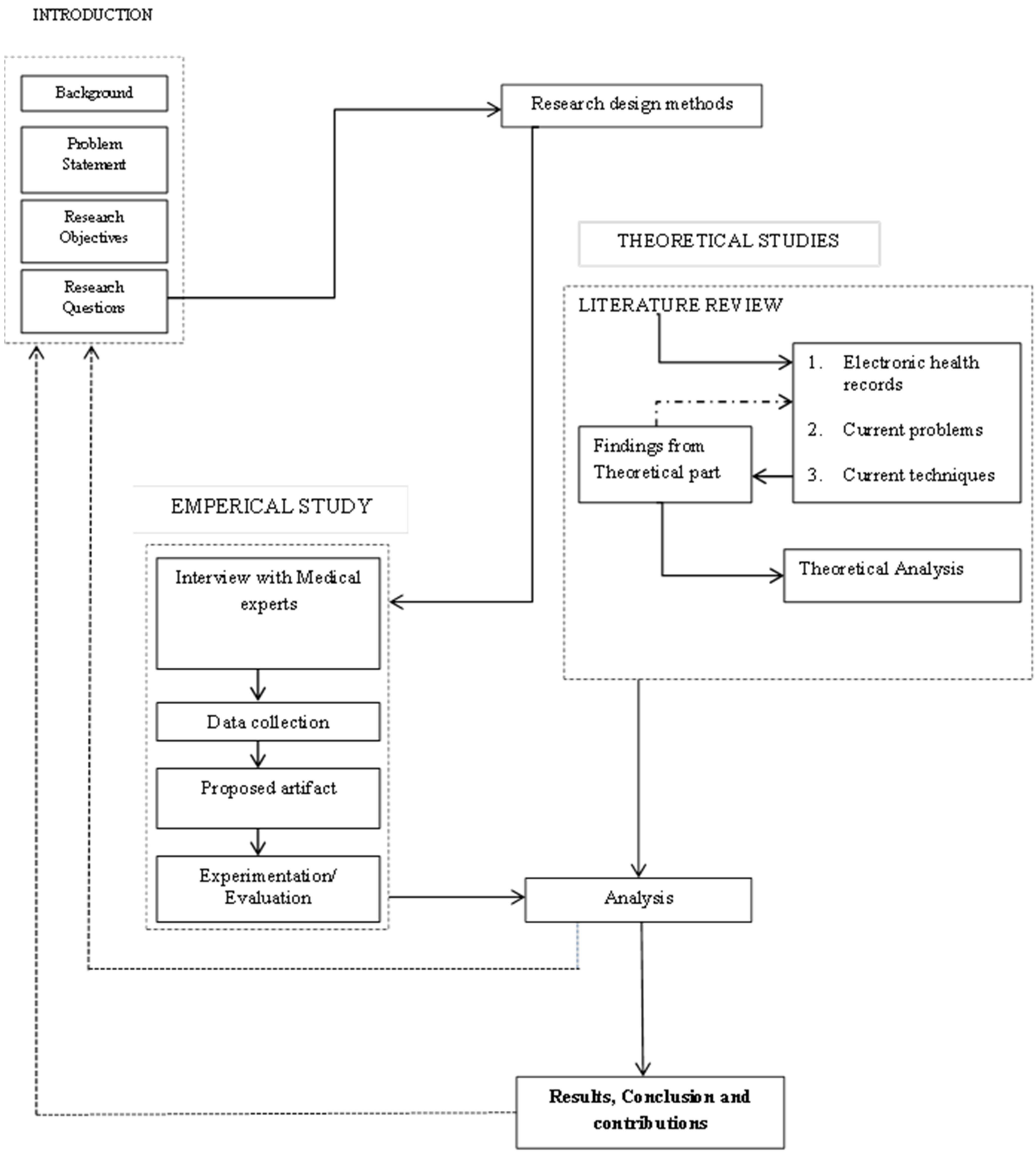

Figure 1.3: Thesis organization

CHAPTER TWO: LITERATURE REVIEW

Because of the prevalent use of electronic health records, people now have the ability to create, access, and store detailed clinical patient information, resulting in an explosion of clinical data (Shickel et al., 2018). This includes a number of clinical narrative text documents, such as clinical notes, discharge summaries, prescription notes, radiology reports, and so on. This information has many practical applications such as allowing doctors and researchers to understand how a patient's health changes over time, informing epidemiologists about the health of the population and identification of cause-effect patterns. In terms of using collected patient data, this poses a real challenge to clinicians who need to examine such huge volume of documentation during care episodes. The time required to retrieve relevant information from these documents using traditional information retrieval techniques is often prohibitive, turning them into cumbersome resources for clinicians. Computational techniques to support clinicians in clinical decision-making process are therefore urgently needed. However, there are still several open research challenges in the clinical narrative text analysis computational techniques that need to be addressed. This has led to emergence of many research interests in systems that help physicians to make clinical decisions using available clinical documentations. In particular a tool which retrieves relevant information from a possibly overwhelming long clinical narrative text documents in electronic form is needed. Electronic health records systems were designed to support physicians in providing timely patient information that support clinical decision-making process. A common task in such systems is retrieving, a medical case of interest, with information helping a physician in formulating treatment plan for the case at hand. Therefore, the goal of such systems is to assist physicians during patient encounters by finding, relevant key information from large collections of documents. In most cases, patient information is described by reports, usually composed of narrative text description about the patient clinical information.

2.1 Challenges of clinical narrative texts

Despite increasing adoption of electronic health records (Khennou, Khamlichi and Chaoui, 2018) and advances in information technology, barriers, such as timely and efficient access to electronic health information, is still a challenge to physicians' using electronic health records (Vrieze et al, 2018). In addition, the emergence of evidence-based medicine (Ruiz et al., 2016) which is also referred to as precision medicine depends on the extraction of knowledge from medical records to provide individuals with the appropriate treatment and faces the same challenges (Ruiz et al., 2016).

Clinical documentation is useful to physicians and researchers involved in patient care and clinical research, respectively. However, extracting insights from clinical documentation, which is mostly unstructured, is one of the greatest challenges in computational medicine (Luque et al., 2018). The use of EHRs generates an overwhelming amount of clinical information about each patient, making it challenging for physicians to quickly locate the most relevant information during care episodes (Singh et al., 2013). In medical practice, physicians always need to get an overview of a patient's clinical history during care episodes. Since, narrative is used in clinical documentation, reviewing it quickly becomes onerous when patient charts become long (Sultanum et al, 2018) and this makes it difficult to find the required information quickly given the volume of texts to be read. For example, doctors in the intensive care unit (ICU) are always dealing with very large volumes of clinical data that they can use to make quick medical decisions. However, the massive amount of information available coupled with inadequate data presentation techniques can overload the cognitive load of even experienced physicians, leading to inaccurate or erroneous actions that endanger patients' lives (Romero et al., 2013). This is a case of information overload problem where users are overloaded with huge volume of data to make decisions from. Empirical studies have shown to have negative consequences in healthcare delivery such as missing important information during the course of care (Singh et al., 2013). The information overload, with physician time limitations inherent in clinical care and human cognitive limitations, have made it difficult for users to use electronic health records (Singh et al., 2013).

Because of the widespread use of the electronic health record (EHR) (Shickel et al., 2018) in medical practice, the availability of electronic clinical data has increased in recent past. This has resulted in unprecedented volumes of clinical data that can be used to support clinical decisions during care episodes (Raghupathi and Raghupathi, 2014) as well as secondary purposes (Assale et al., 2019) such as pharmacovigilance (Henriksson, 2015), phenotyping and clinical workflow optimization (Murff et al., 2011), (Rochefort et al., 2015), and quality control (Hsu et al., 2016). However, it is difficult to use this data as most of them are in unstructured form (Assale et al., 2019), (Zeghdaoui et al., 2018) where queries cannot be executed against so as to get summary view of the content or certain details of interest as in structured data. While some patient data is in a structured form in the electronic health records, useful information about patient management remains hidden in unstructured clinical notes (Mohamed et al., 2018), making it difficult and time-consuming for doctors to review makes their usual clinical encounters (Liang, Tsou, and Poddar, 2019). It is easy to use automated tools to extract data from structured data in electronic health records (Knake et al., 2016), however most data often exist as unstructured free text with lack of easily recognizable data elements (Kimia et al., 2015). In addition, there is the problem of information overload in healthcare delivery (Rand et al., 2018), due to abundant availability of detailed patient clinical data where physicians have access to make decisions from (Rand et al., 2018), (Feyisetan, 2012). As a result, physicians are faced with complex medical records that describe a complex patient history on the basis of which they must make treatment decisions (Smith, 1996). Making decisions using the available records in electronic health records is therefore challenging, because synthesizing the information stored in clinical documents requires more time to read (Deng and Denecke, 2014). It is increasingly becoming a bottleneck for doctors and researchers who want to use clinical information for patient care or research. Therefore, manually reviewing clinical documents such as patient medical chart becomes onerous when patient charts become long (Sultanum et al, 2018). When patients are monitored over a long period of time, at each appointment it is crucial for a physician to get an overview on the progress and changes in the patient status promptly (Deng and Denecke, 2014). Reviewing a patient's clinical history through reading can be challenging especially when the patient has a lengthy clinical record. In our contemporary society, there is increasing prevalence of chronic diseases (WHO, 2014), (Pivovarov and Elhadad, 2015) with patients having long medical histories. Most chronically ill patients often have a lot of records which are challenging to coherently present (Christensen and Grimsmo, 2008). In the care of chronic diseases, data is accumulated over long periods of time and doctors have to access and analyse it during the care episodes. As a result, there is a need to improve how clinical information is organized and presented to doctors in order for doctors to answer questions about a patient case and reduce information overload (Rand et al., 2018). (Covell, Uman and Manning, 1985). The problem of information overload in healthcare is still unsolved, and it is the main issue addressed in this thesis. The following are the specific challenges, as described in the preceding section:

i. Lack of an effective tool for classifying clinical sentences in long clinical documents into predefined semantic classes
ii. Presenting important key clinical information so that the user can immediately get a glimpse of the main topics in long clinical documents i.e., making clinical information visible so that it can be better accessed.

During care episodes, a doctor can benefit from a system for quickly retrieving and visualizing relevant information from a patient's medical record. We propose a text classification and visualization model that employs deep learning and a cluster map to support clinicians in easily classifying and visualizing the key elements of a chart.

Previous efforts to address this problem include methods such as the use of medical ontologies (Beez, Humm & Walsh, 2015), (Ijcsis, 2018), (Arbabi et al., 2019). The most widely used ontology is SNOMED-CT (Systematized Nomenclature of Medicine- Clinical Terms) (Arbabi et al., 2019) used to structure relationships of medical concepts. It is used in electronic health systems to summarize patient clinical records captured during patient encounters. Other ontologies include ICD (International Classification of Diseases), MeSH (Medical Subject Headings), UMLS (Unified Medical Language System) and RadLex. As more and more patient health records become electronic, clinical concepts are extracted by mapping clinical notes to unified medical terminologies such as UMLS, SNOMED-CT. This therefore converts unstructured clinical narrative texts into structured, codified format which is more suitable for further information retrieval, including search functionalities. However, creating medical ontologies is expensive and time consuming (Trivedi et al, 2018), (Trivedi, 2015). In addition, ontologies rely on domain knowledge that is extremely expensive and difficult to capture and formalize (Musen, Shahar, and Shortliffe, 2006).

Table 2.1 ICD-10 codes for congestive heart failure: source (Wang et al., 2019)

ICD 10 code	Description
I110	Hypertensive heart disease with heart failure
I420	Dilated cardiomyopathy
I423	Endomyocardial (eosinophilic) disease
I424	Endocardial fibroelastosis
I425	Other restrictive cardiomyopathy
I426	Alcoholic cardiomyopathy
I427	Cardiomyopathy due to drug and external agent
I428	Other cardiomyopathies
I429	Cardiomyopathy, unspecified
I430	Cardiomyopathy in infectious and parasitic diseases classified elsewhere
I431	Cardiomyopathy in metabolic diseases
I432	Cardiomyopathy in nutritional diseases
I438	Cardiomyopathy in other diseases classified elsewhere
I500	Congestive heart failure
I501	Left ventricular failure
I509	Heart failure, unspecified

Other approaches which are used to address the above problem include clinical text summarization (Mishra et al, 2014), (Feblowitz et al, 2016), (Aramaki et al., 2009) clinical text classification (Shekharet al., 2015), (Kenei et al., 2019), (Lopez et al., 2019), (Wang et al, 2019) and more recently clinical text visualization (Yerebakan et al, 2018), (Sultanum et al, 2018), (Kenei et al, 2018). The problem of growing information overload in our contemporary society is more serious, when one considers the cognitive limitations of the humans. The processing speed of the human brain is fixed, but the amount of information that can be generated is limitless. Looking for information in narrative text documents is often performed by humans in many fields. Since such tasks are usually beyond the capability of keyword search, it is always laborious and time consuming to do it manually and this calls for computational tools. Therefore, there is need for healthcare professionals working with healthcare data to have better support tools to cope with ever growing digital clinical data (Rind, Wagner and Aigner, 2019). In particular, there is need for techniques which can be able to retrieve, organize and present facets of relevant clinical data that can satisfy physicians' information needs without overwhelming them with extraneous information. In order to address this problem, we proposed an alternative visual technique of looking and presenting key information by exploring the sense of sight which can be described more specifically as document visualization. Gan et al (2014), defines document visualization as "a class of information visualization techniques that transforms textual information such as words, sentences, documents, and their relationships into a visual form, enabling users to better understand textual documents and lessen their mental workload when faced with a large volume of available textual documents". When reviewing past patient histories in order to understand each patient's health status, clinicians are finding it difficult to keep up with the growing volume of electronic clinical data generated in electronic health records in modern medical practice. Many studies have been conducted in an attempt to solve this problem by utilizing data visualizations; however, no particular strategy has been widely adopted. In addition, there is no study which has investigated how clinical narratives should be organized within a clinical document to facilitate visualization and easier retrieval of information. No studies, however, have tried to visualize clinical document with SOAP-oriented patient documentation.

From the literature, leveraging digital healthcare data generated in electronic health records and machine learning techniques to address the above challenge comes with a multitude of data-science challenges that impede development of efficient models. The state of the art relevant to this work comprises two clearly defined research areas:

i. Clinical document classification using deep learning models

ii. Clinical document visualization

2.2 Information retrieval

Computer systems store typically store data using a coded format. However, in clinical domain some information such as clinical notes cannot be codified and is therefore stored in electronic health records as narrative free text. These unstructured narrative texts have been shown in the literature to contain useful information compared to structured data. However, due to their unstructured nature, retrieving and extracting information from clinical narrative texts in electronic health records is a difficult process. The objective of information retrieval support system is to provide the techniques that support users to in finding useful information text documents. In this study, we reviewed the literature in order to identify information retrieval techniques that have been used for clinical narrative texts. We also explored different techniques that have proven to work in obtaining important information from unstructured clinical texts.

Information retrieval entails searching and extracting information from texts (Sanderson et al., 2010). In medical field, information retrieval is the process of obtaining data from patient's clinical narrative texts. It has been demonstrated that electronic health records help doctors' better retrieve information from clinical narrative texts (Tange et al., 1998). However, no research has looked at the best way to organize data for this purpose. In the contemporary medical practice information is retrieved by physicians from clinical texts in electronic health records. In order to make decisions, doctors frequently seek information from prior clinical episodes. However, due to the large amount of patient records available, search process is challenging (Plaza and Díaz., 2010). One such technique is "Latent semantic indexing" (LSI) that has been used to extract information from clinical texts. It examines documents to identify latent relationships between words or semantics to enhance comprehension of the information retrieved using singular value decomposition (SVD) technique to scan the narrative text and identify the relationships between the concepts and terms in the texts (Dumais., 2004). Therefore it is used to identify the semantics of the terms in clinical texts. Though it has been proven effective, it has one major limitation, inability to effectively extract information from massive document sets. To address this limitation, a number of researchers such as (Al-Qahtani, Katsigiannis and Ramzan., 2021) have proposed some improvements on this technique. Yousefi, Mastouri and Sartipi (2009) developed a model that extracts and retrieve information from clinical texts using scenario-based data with the ability to clarify the relationships between illnesses, symptoms, and other relevant clinical information. Popescu (2010) proposed a technique that uses general word sequencing, based on a dynamic algorithm and implemented using the Smith-Waterman model's fuzzy variant. Li (2020) proposed a Smart Search (technique to improve the effectiveness of patient information retrieval from clinical narrative texts. Other techniques include Electronic Medical Record Search Engine (EMERSE) (Hanauer., 2006), the StarTracker (Gregg et al., 2003), the MorphoSaurus (Markó, Schulz, & Hahn., 2005), CISearch (Natarajan et al., 2005) and the The Queriable Patient Inference Dossier (QPID) (Campbell et al., 2012). According to Tange et al (1998), information retrieval from clinical narratives involves two steps; looking for a labelled section and reading information in that section. We adopted this approach by classifying clinical texts into different sections that enables users to look for information in different labelled clusters.

2.3 Clinical document classification

Automatic document classification is a technique which is widely used to categorize documents into predefined classes often called thematic labels (Sebastiani, 2002). In the clinical domain, the unprecedented volumes of electronic clinical notes in electronic health records have led to increase demand for automated document classification techniques, to help leverage the utility of clinical narrative texts (Charles, Gabriel, Searcy, 2015). Prior research in the literature has shown promise in automating classification of clinical texts to support clinical decision making. The automated classification of clinical sentences in clinical narrative texts into pre-defined classes could assist in segmenting clinical narrative text into different facets of information. Clinical notes are written in natural language in medical practice and are then used to answer clinical questions by providing detailed patient conditions, clinical rationale, and clinical conclusion (Weng et al., 2017) thus making them a valuable resource for answering clinical questions by providing information which is typically unavailable from other parts of the electronic health record (Weng et al., 2017). Currently, research in automated document classification is a hot topic, with the goal of maximizing the utility of narrative clinical notes (Charles, Gabriel, Searcy, 2015).

In the last few years, artificial neural networks have shown remarkable success in many classification tasks such as image recognition (Krizhevsky, Sutskeve and Hinton, 2012), (Simonyan and Zisserman, 2015), ultrasonic signal classification (Meng et al, 2017) and biological image classification (Affonso et al, 2017). Recently, they have shown similar results in NLP tasks (Lopez and Kalita, 2017) such as text classification (Schwenk et al, 2017). Kim (2014) showed that a simple neural network with little hyper parameter tuning and static vectors achieves excellent results on several benchmarks and improves the state of the art on four out of seven tasks. The recurrent neural network (RNN), a type of neural network that explicitly exploits sentence structure, has been shown to be an effective and promising tool for learning sentence representations (Cheng, Yuan and Yang, 2018).

The primary goal of neural networks is to extract features and classify them as one jointly trained task (LeCun et al., 1998). This concept has evolved over time, most notably by employing multiple levels of convolutions and pooling to sequentially extract a hierarchical representation of input data (Zeiler and Fergus, 2014). He et al. (2016a,b), for example, used a model with more than 150 layers, which produced the best results. Most NLP approaches consider words as basic units that have been boosted by the introduction of continuous representations of words known as word embeddings (Bengio et al., 2003) to achieve the best results. These are low-dimensional vectors obtained using unsupervised techniques on large unlabelled corpora, where words from the vocabulary are mapped to vectors of real numbers (Madhyastha, 2019). Their objective is to capture syntactic and semantic properties of words and resolve sparse and high dimensional feature problems inherence in natural language processing (Chiu & Baker, 2020).

Distributional word embeddings are state of the art techniques for natural language processing tasks (Mikolov et al., 2013), (Wang, Nulty and Lillis., 2020). However, the best way to represent a sequence of words, such as a whole sentence with complex syntactic and semantic relationships, is less clear. The current mainstream approach is to treat a sentence as a sequence of tokens (characters or words) and process them with a recurrent neural network (RNN). Tokens are typically processed sequentially, from left to right, with the RNN expected to "memorize" the entire sequence in its internal states. LSTMs are the most widely used and successful RNNs (Hochreiter and Schmid, 2016). According to the literature, neural networks used in sentence representation fall into three categories: sequence models, convolutional models, and recursive models. In text classification tasks (Wang et al., 2016; Zhang et al., 2017) and many other classification tasks, recurrent networks have demonstrated state-of-the-art performance. They take each word as input and combine it with its previous state to generate the compositional result of the entire sentence. The result of the composition is a fixed-length vector containing rich semantic information, which is then used for classification tasks. From the literature, there are various conventional machine learning models that have been used for text classification tasks. Some of the popular examples include Support Vector Machine (SVM) (Joachims, 1998), Naive Bayes (Jurafsky and Martin, 2009), K-Nearest Neighbors (Huang, 2008) etc. Supervised Machine Learning (ML) techniques such as in (Uzuner, Solti and Cadag, 2010) and (Kholghi et al., 2015) have been widely used to facilitate information extraction and classification of clinical documents and they have shown promising results (Hassanzadeh et al., 2018). However, to build effective classifiers, these approaches require a lot of labelled data to effectively capture useful information from clinical texts. In particular, traditional text classifiers rely on manual human-designed features, such as dictionaries, knowledge bases and special tree kernels (Lai et al., 2015). Creating such labelled data is expensive, particularly in clinical domain as it requires significant efforts from highly qualified and busy health professionals (Hassanzadeh et al, 2018a). Limited amounts of labelled data have presented one of the major challenges in applying conventional machine learning techniques in the healthcare domain (Hassanzadeh et al., 2018b). Classification tasks usually involve feature engineering, feature selection and using different machine learning algorithms. For feature engineering, traditional algorithms most widely used feature is the bag-of-words feature (Lai et al., 2015) which has limitations such as large feature dimension and sparse representation.

However, recent advances in artificial neural networks, particularly deep learning, have paved a new path for applying deep learning techniques to clinical document classification challenges. Deep learning techniques have recently been used on a growing number of data sets generated by electronic health records (Shickel et al, 2018). Norgeot et al. (2019), for example, developed a deep learning model to predict disease activity in patients with Rheumatoid Arthritis at their next clinical visit in order to assess inter hospital performance and model interoperability strategies (Norgeot et al., 2019). Norgeot, Glicksberg and Butte (2019) argued that deep learning can help create smarter healthcare systems that can make best treatment decisions computationally by learning from health data. From their findings they concluded “that building accurate models to forecast complex disease outcomes using EHR data is possible and these models can be shared across hospitals with different EHR systems and diverse patient populations”.

Deep neural networks have yielded state-of-the-art performances without using any manual features (Dernoncourt et al., 2016). Compared to conventional approaches, the classification model can be fine-tuned on a new dataset without the overhead of manual feature engineering, as long as some labels for the dataset are available (Lee, Dernoncourt and Szolovits, 2017).

In the clinical domain, current state-of-the-art approaches use a multi-layer convolutional neural network for high-level semantic understanding of electronic medical records (Yang et al., 2018), which can then be used for disease diagnosis (Norgeot et al, 2019). Convolutional neural networks have proven to be remarkable in text classification tasks, achieving state-of-the-art results (Zhang and Wallace, 2017), and have been successful in many fields such as computer vision (Szegedy et al., 2015) and natural language processing (Kalchbrenner, Grefenstette, & Blunsom., 2014), (Shu, Xu, and Liu, 2017). In predicting health-related data, a Google deep learning model recently outperformed traditional methods of sifting through voluminous EHR data (Rajkomar et al., 2018). Sentence classification (Kim, 2014, Kalchbrenner 2014, Zhang and Wallace, 2017) is a classification task that involves assigning meaningful classes to text segments of various lengths, such as symptoms, diagnoses, and so on. The task of labelling natural language sentences and expressions with thematic categories from a predefined set is known as sentence classification. Based on the evidence provided by a set of labelled sentences, this activity is carried out using a classifier that has been trained to learn the mapping between sentences and categories (training set).

Convolutional neural networks have been shown to have an advantage in feature extraction and expressions (Krizhevsky, Sutskever, and Hinton, 2002). (Zeiler and Fergus, 2014).

They don't need hand-crafted features because they can self-learn from the data they have (Yang et al., 2018). Deep learning methods learn these features directly from data, unlike traditional machine learning techniques, that rely on hand-engineered feature extraction from inputs (Chartrand et al., 2017). They're frequently used with distributional word representation, which uses a continuous vector space model to represent words in texts (Mikolov et al., 2013). As a result, it is advantageous because the model does not require a large number of rules or knowledge base to guide how it makes decisions, and the model can extract useful information from electronic medical records automatically through self-learning (Yang et al., 2018). Several algorithms for classifying clinical text documents have been developed, according to the literature. These approaches range from identifying different sections of documents to classifying each sentence type using clinical text documents such as radiology reports and outpatient medical charts.

2.4 Clinical document visualization

The information overload problem affects healthcare delivery. A lot of digital clinical narrative texts in electronic health records overwhelm physicians during care episodes. In this context, the use of data visualizations to support information extraction from clinical texts is increasing. According to Shneiderman (1996), humans cannot quickly process a large set of documents, and so some proposed systems use some sort of filtering mechanism, such as a visual overview and then details on demand. There are many studies that have dealt with text visualization. These can be categorized into three groups; document content visualization,

visualization of document relationships and multifaceted text visualization (Cao et al., 2011). Techniques for visualizing document content serve to summarize the content of a document or a document collection. Common examples include tag cloud (Hassan-Montero and Herrero-Solana, 2006) and its variants Wordle (Viégas, Wattenberg and Feinberg, 2009) and Word Cloud (Clark, 2009). Others include Cards (Strobelt et al., 2009), Topic islands (Miller et al., 2009), ThemeRiver (Havre, Hetzle and Nowell, 2000), WordTree (Wattenberg, M., & Viégas) and PhrasNet (Ham, Wattenberg, and Viégas, 2009). Visualization of document relationships techniques displays relationships between documents in a collection (Cao et al, 2011). Examples include InfoSky (Andrews et al., 2002), Exemplar-based visualization (EV) (Chen et al., 2009) etc. Multifaceted text visualization uses visual techniques to show the document content and their relationships (Cao et al, 2011). Examples include ContexTour (Lin et al., 2010) and FacetAtlas (Cao et al., 2010).

Figure 2.1: Sample tag Cloud: source (Torres et al., 2021)

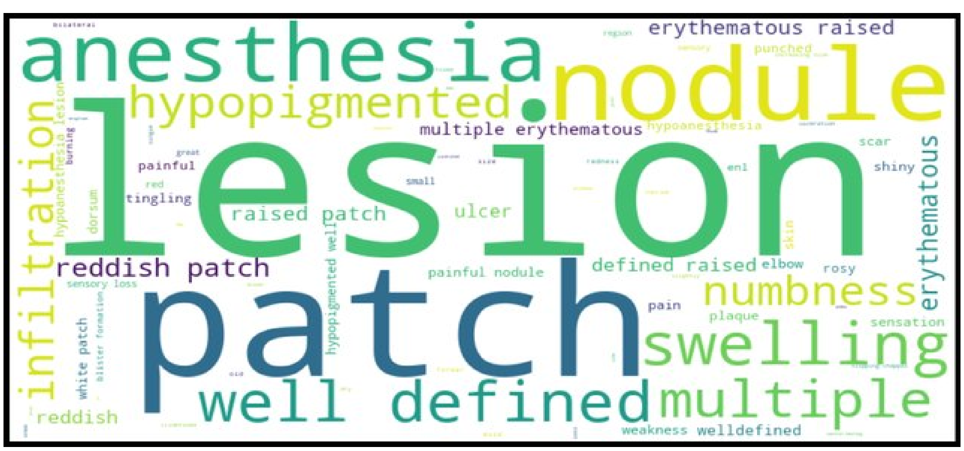

Figure 2.2: Sample Word Cloud of Clinical text: source (Mehta et al., 2020)

The majority of the current state-of-the-art visualization techniques described in the literature are aimed at data from electronic health records (Hood and Flores, 2012). The most common method is to use TimeLine, a visualization tool that allows physicians to browse information chronologically by retrieving clinical data and presenting it in a hierarchical and timeline-based structure (Bui, Aberle, and Kangarloo, 2007). There are several techniques which have been proposed in the literature for visualizing clinical documents. In most attempts, relevant information, such as diagnoses, medications or medical procedures are highlighted in the text (Deng and Denecke, 2014). Some of the common techniques include charts and diagrams which can be used to show relations between terms, categories or expressions (Ballstedt, 1999). For HIV cohort data, Blevins et al (2016) created an interactive visualization tool. Grasso, Joshi, and Siegel (2016) created a visualization system that extracts pain severity events from clinical text using ontology-based semantic search and then displays them in a visualization to track pain progression over time.

By analyzing a number of visualization projects, Kopanitsa et al (2012) comprehensively reviewed the state of the art in clinical data visualization. He outlined the requirements for a data visualization method based on ISO 13606. (Kopanitsa et al, 2012).

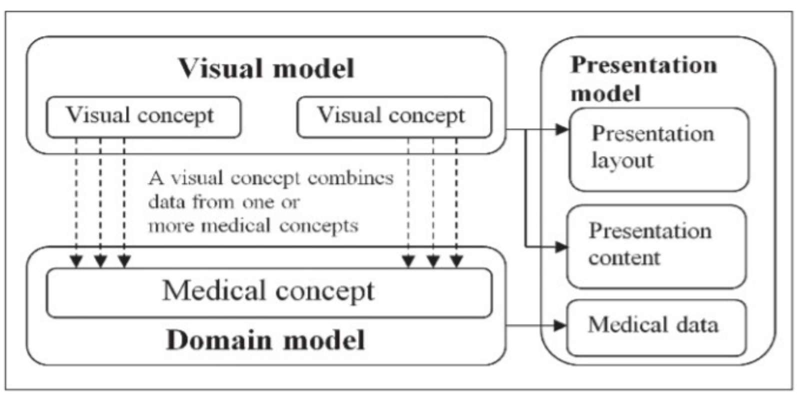

Figure 2.3: Dual model architecture for medical data visualization
Adapted from (Kopanitsa et al, 2012)

Rind et al. (2013) compared a number of state-of-the-art visualization research systems for EMR and separately provided examples of visualizations produced by commercial systems in a detailed review. Roque et al. (2010) also included comparisons of the major clinical data visualization systems. West et al. (2014) conducted a systematic review of the literature from 1996 to 2013 and published an article on the use of visual analytics to aid in the analysis of complex clinical data (Caban et al., 2015). Boyd et al. (2017) investigated how data visualization could transform healthcare and discovered that the field's maturity is still in its infancy (Boyd et al., 2017). A notable mode of visualizing clinical data is the Flowsheet (Waitman et al., 2011), which is mostly used in ICUs based on commercial EMR systems. It contains key patient information which includes medical variables over a given time and the ability to show trends and abnormal values (Ruan., 2019). Ledesma et al (2019), developed information visualization solution which visualizes clinical data in chronological order. Their solution was primarily based on a timeline, dubbed "Health Timeline" to emphasize the importance of time in clinical data. Their system organizes and displays clinical information in an interactive timeline with visual enhancements to make it easier to read (Ledesma et al., 2019). From their empirical studies, they found out that the solution improved understanding of clinical data and helped users recognize complex patterns in data.

2.5 Deep learning algorithms

Deep Learning algorithms are machine learning techniques that are inspired by the structure of the human brain. Employing what is called an artificial neural network (NN), these algorithms use multiple layers of neurons to solve increasingly more complex features from input data (Cook, 2020).

2.5.1 Convolutional Neural Network

Convolutional neural network (CNN) construction involves stacking many layers of neurons together, much like any other neural network. The depth of the network increases with the number of layers. There are numerous convolutions, pooling, and fully linked layers in a typical CNN design. The number of layers of each kind, the layer order, and the hyper parameters for each type of layer, such as the receptive field size, stride, and number of receptive fields for a convolution layer, must all be decided by the network designer when building a CNN. Convolutional neural network uses multiple layers in its architecture. The figure 2.4 below show a neural network with three layers.

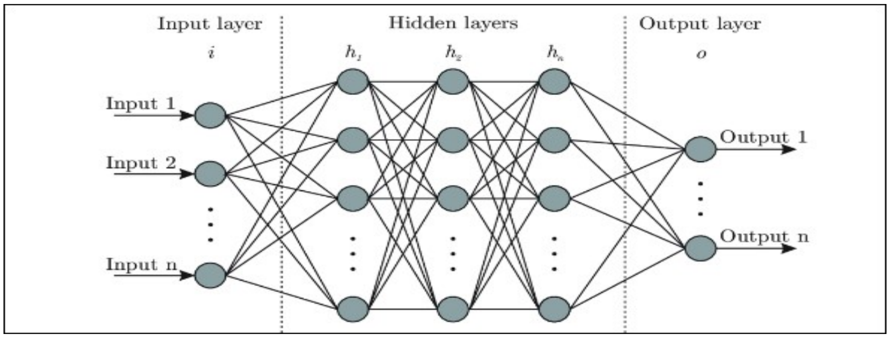

Figure 2.4: Artificial Neural Network with three hidden layers: source (Bre et al., 2018)

The following are the layers used to build convolutional neural network architectures.

i. **Input layer -** The input layer feeds the network's second layer, which is often the convolutional layer, with the input data.

ii. **Convolution layer-** A convolution layer is an important component of convolutional neural network architecture that performs feature extraction. It is made up of a combination of linear and nonlinear operations, i.e., convolution operation and activation function (Yamashita et al, 2018). The purpose of a "convolution" in the case of our proposed model is to extract features from the clinical narrative text document. It is the convolution layers that learn the features that are suitable for differentiating different clinical concepts in the clinical document. The local features required for this are learned by initial convolutional layers whereas the deeper layers learns the global feature required for differentiating between different medical sentences. Using a set of kernels or filters referred to as receptive fields, each convolution layer applies the convolution process on the outputs of the preceding layers. The operation of convolutional layers is illustrates figure 2.5 below. The convolutional layer's input matrix is on the left, the kernel input matrix is in the middle, and the convolutional layer's output matrix is on the right.

iii. Convolution of the kernel over the input layer produces the output.

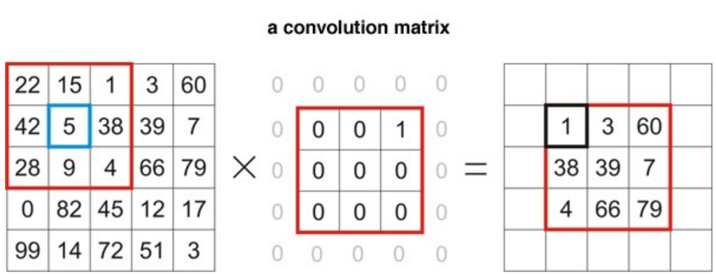

Figure 2.5: Convolutional operation

iv. **Pooling layer -** By splitting the input matrix into smaller matrices and choosing one value to represent each of the smaller matrices, the pooling layer is used to down-sample the input arrays (feature maps). There are two types of pooling layers used: the max pooling and mean pooling layers. In max pooling the maximum value in the sub matrix is taken to represent the sub matrix whereas in mean pooling the mean of the sub matrix is taken. Scherer et al (2010) demonstrated that max pooling is more effective than mean pooling in classification tasks. Therefore, we have used max pooling in our proposed model. Figure 2.6 is an example illustrating the max pooling operation. The input matrix in this example is of size 4x4 and is divided into 4 sub matrices. The max value in each of the sub matrix is then taken and the output matrix is created using these values.

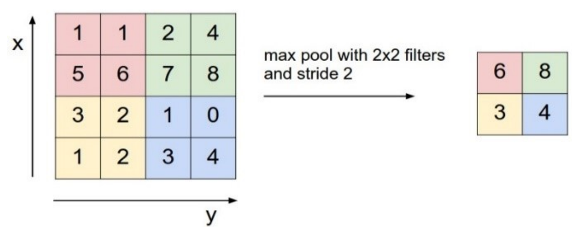

Figure 2.6: Max pooling

v. **Fully connected layer (FC) -** The final convolution or pooling layer's output feature maps are typically flattened, or converted into a one-dimensional (1D) array of numbers (or vector), and connected to one or more dense layers, also known as fully connected layers, in which each input and each output are connected by a learnable weight.

vi. **Activation layer -** Activation layer is an important component of convolutional neural networks used for adding non-linearity to the neural networks. The outputs of linear operations like convolutions are applied to this nonlinear function. There are many activation functions available such as tanh(x) and ReLu. Nair and Hinton (2010) proposed an effective activation function called ReLU. ReLu is a technique that is commonly employed in hidden layers nowadays and is perfectly linear for positive inputs, passing them through unchanged, while blocking negative inputs (i.e., evaluating to zero) (Chartrand et al., 2017).

vii. **Sigmoid layer -** Finally, a sigmoid activation is given to the output layer. The final layer of the convolutional neural network is called the sigmoid layer. This layer is responsible for calculating the likelihood that each of the input's five classes will be represented by the input.

Many neural network models use a softmax layer to convert the class activation magnitudes to pseudo-probabilities.

2.5.2 Recurrent Neural Network

In the recent past, Residual Network (ResNet) has shown state-of-the-art performance in many classification tasks (Deng et al., 2009). ResNet has the ability to train extremely deep networks more than 1000 layers (He et al., 2015b). It uses identity links that allow information to flow across layers without attenuation that would be caused by multiple stacked nonlinear transforms, resulting in improved optimization (Srivastava et al., 2015). Recently, residual neural networks have been found to be successful in learning text representations and have shown state-of-the-art performance in text classification tasks. They have been shown to be efficient in learning sequential data, such as natural language texts (Jackson et al., 2017), (Swartz et al., 2017). Figure 4.6 shows a typical residual neural network(RNN) architecture ; where the output of the 1st convolutional layer x_1 is the input of the 2nd convolutional layer via activation layer (tanh), x_1 will be summed directly with the output of the 2nd convolutional layer x_2 before activation layer (tanh). The main objective of ResNets is to connect layers with shortcuts, thus avoiding problems with vanishing and exploding gradients. These problems can occur in very deep networks. The shortcut connections have the ability to explicitly fit these layers to a residual map using identity transformation. The residual block is defined as:

$$x_2 = F(x_1) \tag{1}$$

$$x_3 = \tanh\big(F(x_1) + \mathrm{id}(x_2)\big) \tag{2}$$

Where

- $F(\cdot)$ function represents Tanh (after 1st convolutional layer) and the 2nd convolutional layer; x_3 is the value after activation,
- $\mathrm{id}(\cdot)$ is an identity mapping function (ResNet);
- $\tanh(x) = (\mathrm{e}^\wedge x - \mathrm{e}^\wedge(-x))/(\mathrm{e}^\wedge x + \mathrm{e}^\wedge(-x))$ (3) , is the activation function for output of Word Residual block (see Fig. 2.7).

If the dimensions of x_1 and x_2 are the same, the last equation will simply change as follows:

$$x_3 = \tanh(F(x_1) + x_2) \qquad (4)$$

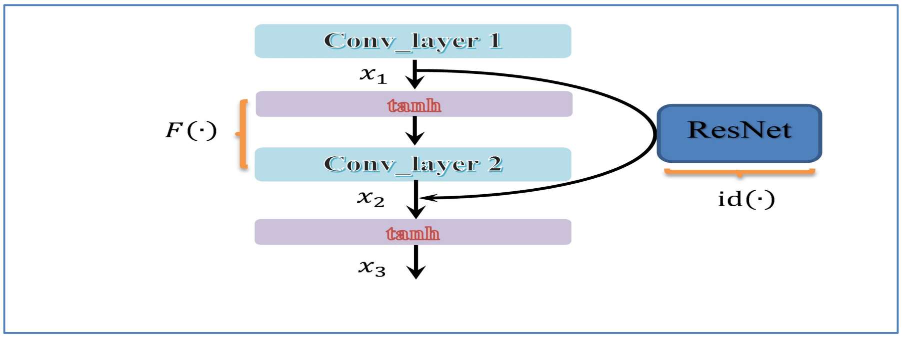

Figure 2.7: Residual and identity mapping in ResNet.

2.6 Distributed vector representation of texts

To solve any text classification problem, the most important issue is how to encode the meanings of individual words and phrases in a form that can be understood by a computer (Johnson, 1999). Researchers have come up with a number of techniques that transform words into points of a Euclidean space of a certain dimension. This process is known as "embedding," and it assigns each word in the vocabulary an unique vector (representing words as low dimensional vector). To build a classification model for text classification, there is need to represent documents in a vector space. Traditional frequency-based methods represent a document using either a bag-of-words, which is a list of the words that appear in the document with their frequencies, or tf-idf (term frequency – inverse document frequency) vector where the word frequencies in the document are weighted with their frequencies in the entire corpus. However, these techniques don't take into account both the words order and the semantic structure of expressions. In the last few years, research in deep learning has propelled the development of a variety of word embedding models trained by neural networks. The most popular models include word2vec (Mikolov et al. 2013a, b), Glove developed by Stanford University (Pennington, Socher, & Manning, 2014) which is an extension to the Word2vec (Brownlee, 2017) for efficiently learning word vector. Other models include Caffe (Jia et al., 2014) and fastText (Bojanowski et al. 2017; Mikolov et al. 2018). These models are commonly referred to as distributed word representations. Word2Vec was the first distributed word representation technique released in 2013(Mikolov et al., 2013b). Mikolov et al (2013b) developed two types of architectures: the continuous bag-of-word (CBOW) and the skip-gram (SG) (Dynomant1 et al., 2018).

2.7 Research gaps

The Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are two examples of deep learning algorithms that have achieved considerable success in the last few years. They are widely used in image processing (Zhou et al., 2015) and natural language processing (Voulodimos et al., 2018). Despite their considerable success, there are still some fundamental issues that have not been resolved. Training deep neural networks is a challenging problem due to vanishing and exploding gradient problems (Yue, Fu and Liang, 2018) for example; a well-known problem is the training of RNNs when learning long-term dependencies (Gustavsson et al., 2013). Training deep learning networks is a challenging problem, because the distribution of each layer's inputs changes when the parameters of the preceding layers change during training (Ioffe and Szegedy, 2015). This makes it challenging to train models with saturating nonlinearities and slows down training by requiring lower learning rates and careful parameter setting. Therefore, the learning and convergence speed in deep neural networks is greatly affected by this problem (Darwish and Nakhami, 2017). This problem is called internal covariate shifting and is addressed by normalizing layer inputs (Ioffe and Szegedy, 2015). Therefore, getting deep neural models to converge within a reasonable time during training is a challenging problem) (Ioffe and Szegedy, 2015). A technique known as batch normalization, that is used to normalize activations in deep neural networks' intermediate layers, was introduced to address this issue. Experimental findings demonstrate that batch normalization can increase deep learning model training speed and accuracy (Bjorck, Gomes, & Selman, 2018). By normalizing the input to the neural network, there is no need to worry about the range of input features. Thus, the gradient descent reduces the oscillations as the minimum point is approached and thus converges faster. Another important fact is that batch normalization reduces the impact of earlier layers on later layers in the deep neural network. Finally, using batch normalization can reduce the impact of earlier layers by keeping the mean and variance unchanged, allowing the network to converge faster.Using Batch Normalization, the neural network is less sensitive to parameter initialization, since outputs are automatically rescaled.

From the literature, previous attempts to address this issue have used batch normalization (Ioffe & Szegedy, 2015), which helps speed up deep neural network training by reducing internal covariate shift. It is currently the most widely adopted technique to accelerate and stabilize training of deep neural networks (Santurkar et al, 2018). However batch normalization has some limitations such as the inability to consider the underlying distribution of the parameters and the nodes (Salimans and Kingma, 2016). It depends on batch statistics for layer wise input normalization during training which makes the estimates of mean and standard deviation of input (distribution) of hidden layers inaccurate for validation due to shifting parameter values(Arpit et al, 2016). Batch normalization has also been shown to require significant computational overheads (Gitman and Ginsburg, 2017).

2.8 Related works

Using visualization techniques to identify and present clinical information in electronic health records has been successful in many studies. From the literature, there are several clinical data visualization techniques that have been proposed by researchers (Lesselroth and Pieczkiewicz, 2011). A detail review in (Rind et al., 2013) found several proposed techniques for visually viewing data in EHRs. Another review by (Roque et al., 2010) compiled a list of data visualization techniques employed for clinical data. This review provides a number of tools that have been design to visualize patient data such as health Lifelines, Lifelines2, KNAVE II, CLEF Visual Navigator, Timeline, and AsbruView (Mønsted et al., 2011). Many review papers have been published in the literature that have studied, investigated, and discussed various proposed various visualization models. The most extensively reported systems are TimeLine, LifeLines/LifeLines2 and KNAVE/KNAVE-II/VISITORS that are used for visualization of Time-Oriented Records. TimeLine is used to present a gestalt view of a patient's clinical history (Bui et al., 2004). The information is organized into categories and shown on a timeline. A lifeline is a timeline visualization technique used to represent an individual patient's temporal events where time is shown on the horizontal axis, while events are displayed on the vertical axis. LifeLines have evolved into LifeLines2, with the ability to accommodate multiple patient records (Hammond, West and Borland, 2015). West et al. (2017) researched on the use of visualization techniques and evaluated various innovative approaches to information visualization of electronic health records (EHRs) such as KNAVE and VISITORS. They found out that few techniques have been put into use to display the large and complex data in electronic health records. KNAVE-II is a smart web based interface that allows users (such as physicians) to visualize and explore time-oriented clinical data (Goren-Bar et al., 2004). VISITORS (Visualization of Time-Oriented Records) is a tool which is also used for visualization and exploration of raw time-oriented data of multiple patients (Klimov, Shahar and Taieb-Maimon.,2010). KNAVE and VISITORS were designed to address the need of large volume of time-stamped clinical information, to help medical professionals and researchers to process multiple time-oriented patient data. There have been many research works in visualizing health data with the aim of extracting knowledge from clinical documents. But most of them are related to the concept of timeline. Several studies have concentrated specifically on techniques based on timelines. Timelines are well-known visual artefacts that help healthcare professionals visualize patients' electronic health records (EHR) over time, according to the literature. Using a concept of a timeline, health timeline was created to provide a visual method to review a patient's medical history (Ledsema et al., 2019). Ledesma et al (2019) extensively studied the use of timelines and their findings show that using the Health Timeline data visualization tool, valuable insights were generated using the proposed criteria. It is used to display health data chronologically (Ledsema et al., 2019). Belden et al (2019) presented a medication timeline with the objective of assisting physician understand a patient's medical history. In recent years, a number of visualization methods such as AsbruView have been developed to visualize patients' clinical records in electronic health records. Visualizing clinical narrative texts of patients records enabling the review of patient clinical history, is still unsolved challenge. To fill this need, we proposed a technique that improves on existing visualization approaches to clearly structure the content of patient chart as well as their presentation on a patient's condition. Traditional linear timelines are increasingly becoming inadequate for handling data graphically since they frequently stretch across several screens, and data contained in EHR tends to grow during care episodes.

2.9 Research Framework

This section describes the theoretical foundation of the study and the resulting conceptual framework.

2.9.1 Theoretical Framework

Theoretical framework is a structure that supports a research study's theory. The theoretical framework presents and discusses the theory that explains why the research problem under investigation arises. A theory's purpose is to create a framework for generating explanations for phenomena.

2.9.1.1 Information foraging theory

Information Foraging is a theory describes how people seek out information. It is based on the food foraging theory, which aids scientists in understanding the elements influencing an animal's food preferences and feeding strategies (Pirolli and Card., 1995). The idea of Information-foraging theory was coined in the 1990s when the amount of information available to the ordinary computer user exploded which arose the need for developing novel techniques for accessing and using the information (Pirolli., 2003). These techniques were aimed at addressing issues with searching and exploring electronically stored information. Drilling down to search information has a limitation that is formally defined in information foraging theory (Pirolli, 2009). Information foraging theory helps in understanding and improving human-information interaction (Pirolli, 2007). It draws parallels between how people search for information and how animals forage for food. It highlights, in particular, the fact that users don't often find information via a strictly linear process. Instead, important information frequently appears in patches that the user must search for using information scent which refers to clues in the user interface (Plaisant et al., 1998). This theory has been applied in healthcare domain to study strategies used by medical practitioners in identifying and retrieving information to support clinical decision making while taking workload and time constraints into consideration. This research was inspired by the success of many information foraging techniques used to improve information retrieval tasks. In this thesis, the notion of enhancing clinical texts is based on the information foraging theory, where the value of data from clinical narrative texts is enhanced by supplying better methods for information identification and retrieval. For example, structuring and organizing clinical narrative texts in a cluster map (with visual cues) supports in fast retrieval of information than a linear of texts and hence support quicker and more accurate decisions.

2.9.1.2 Cognitive load theory

Human and technical factors contribute to the problems associated with using clinical narrative texts in electronic health records. However, problems involving human factors are more likely to affect patients. One of the human factors that contribute to these problems is cognitive load. According to this theory, people's capacity to process and understand information is limited (Mayer and Moreno., 2003). The mental effort required to execute a task within a specific period of time is known as cognitive load (Oviatt., 2006). There are three types of cognitive load; intrinsic, extraneous and germane. Intrinsic cognitive load describes how complex the work is., extraneous refers to distractions that put more mental strain on the brain and Germane involves connecting new knowledge with the information already stored in the long term memory (Orru and Longo., 2018).

During clinical encounters with patients, a physician always considers various information elements of the patient at hand such as current symptoms and previous diagnosis. While drawing on earlier knowledge, the person keeps this information in working memory. However, the quantity of information that must be processed has a significant impact on working memory. A physician will rely on the EHR in the context of modern medicine to retrieve information in order to create a mental model that takes the components of the issue into consideration. The abundance of clinical narrative texts in electronic health records (EHRs) has resulted in a need for automated techniques to lessen the cognitive load on physicians using clinical narrative texts in current EHR systems. The Cognitive Load Theory offers a framework for understanding physician's cognitive load and its impacts on working memory and, ultimately, the task of reading clinical narrative texts. This theory is relevant to our study because the tasks performed by physicians involve integrating multiple elements of information, which cognitively loads their working memory and impairs performance. Our artefact supports rapid information access and retrieval by presenting clinical information through clustered data views with visual cues to help users quickly review through the presented information facets. Our primary objective stemmed from a clinical requirement to reduce physicians' cognitive overload in reviewing patients' clinical narrative texts in EHRs. This technique structures a linear text into nonlinear text where the reading path is nonlinear and non-sequential; providing, the reader selective reading of texts. This contrasts with linear text where a reader is forced to read texts sequentially, from beginning to the end.

2.9.1.3 Cluster hypothesis

According to the cluster hypothesis, documents that are closely related to one another are often relevant to the same information needs (Van Rijsgergen, 1979). Documents that are closely related to one another are often relevant to the same information needs. This hypothesis has sparked a significant amount of research in the field of information retrieval resulting in huge body of research work. In this thesis, this hypothesis helped us formulate a solution that puts together texts into clusters that discusses similar information. The presentation of results is based on the cluster hypothesis, which asserts that documents with a comparable relevance to a given query group together. We proposed a retrieval system where clusters of clinical narrative texts are created using text classification. All texts in a cluster are represented in a cluster because they have been classified with a common label. This therefore creates a document structure where texts are transformed into a logical cluster map structure to facilitate searching for information. We hypothesized that improved information retrieval would be achieved when clinical narratives are structured into labelled clusters.

We consider a set of n information facets $F = \{f_1, f_2 \dots\dots\dots\dots f_n\}$ where each cluster f_i is made up of a set of sentences S= $\{s_1, s_2 \dots\dots\dots\dots s_{|G_i|}\}$. Consider a set of n user information queries. $Q = \{q_1, q_2 \dots\dots\dots\dots q_n\}$. In response to each query in Q, cluster-based retrieval seeks to retrieve one or more facets in F to satisfy the user query.

The task is to label sentences based on their semantic information and match them to respective clusters. The objective of this approach is to reduce the time of seeking information process. Instead of processing the whole document, only the relevant clusters to the user information needs are explored.

2.9.1.4 Cluster-based information retrieval

Cluster-based information retrieval is one of the information retrieval (IR) techniques that extracts, organizes, and categorizes texts based on their similarities (Hussein, Hamzah and Toman., 2020). It is based on the hypothesis that similar documents will match the same information needs (Rijsbergen., 1997). In this paper, a technique based on cluster-based retrieval is adopted to develop a system for classifying and visualizing narrative texts. The project is implemented through two stages. In step 1, classification is implemented to label texts into distinct classes, while in step 2; labeled texts are visually displayed to support information retrieval process on information classes that are deemed relevant to specific user information needs.

2.9.1.5 Data normalization techniques theory

In machine learning, normalizing input data before passing it to the input layer is standard practice. This is done to make sure that all of the data is at the same level. This aids the convergence of gradient descent-based models. Normalizing the input data or features before training a neural network model can help speed up the process (LeCun et al., 1998).

Data normalization can be done in two ways:

i. Scaling all variables values to a range e.g. [0, 1]. This is achieved using equation 3 shown below.

$$\boldsymbol{X_{new}} = \frac{\boldsymbol{X - X_{min}}}{\boldsymbol{X_{max} - X_{min}}} \qquad (\mathbf{5})$$

In this method, the inputs to neural networks are normalized to a range e.g. [0, 1]

ii. Scaling data to have a mean of 0 and a variance of 1: This is accomplished using equation 4 shown below:

$$X_{new} = \frac{X - \mu}{\sigma} \qquad (6)$$

Where μ and σ are the sample mean and standard deviation respectively. In this method, the inputs to neural networks are normalize so that the values have mean =0 and variance =1. This technique changes the distribution of input data in such a way that it has zero mean and unit variance i.e. it transforms inputs so that they are standardized, meaning that they will have a mean of zero and a standard deviation of one.

2.9.1.6 Information visualization theories

From the literature, there is no well-established underlying theory for information visualization, making it difficult to test and justify the tools developed and determining the value of novel visualization techniques before they are used. As a result, there is a great deal of concern in the field about the lack of theoretical support for the numerous remarkable and practical tools that researchers in information visualization build, deploy, and assess. A theory's function is to offer a framework for explaining phenomena. The evaluation and prediction of events, in this instance, user insight or knowledge of visualization and usage, may then be done using this framework. With the aid of an information visualization theory, we would be able to assess visualizations in light of a pre-existing framework and forecast the outcome of a novel visualization technique.

2.9.2 Conceptual Framework

Electronic health records generate massive amounts of clinical narrative texts that are usually not explored in depth by physicians. Classification and visualisation techniques could support information extraction and retrieval. We proposed a technique for classifying and visualizing clinical narrative texts in accordance with several informational features. After review of the key literature on clinical text visualization, as well as the influential work of designers like Tufte, a prototype was proposed that was designed to emphasize the different facets of information in a clinical narrative text document. Our proposed model provide a novel technique aimed at automatically extracting relevant information facets from texts, in the context of SOAP documentation format, and connecting these facets of information so as to obtain a graphical cluster map.

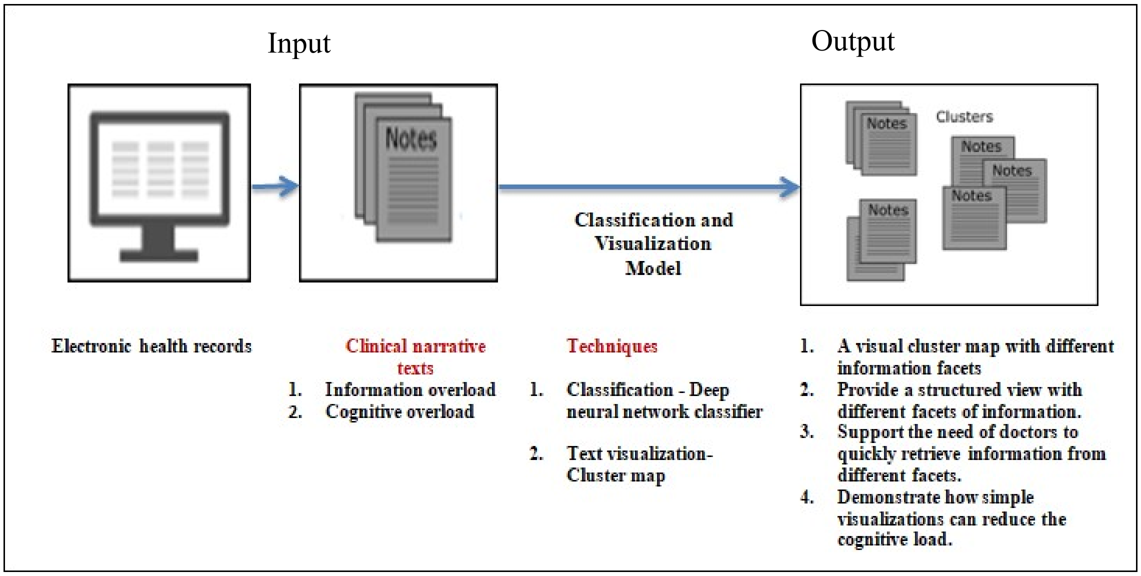

Figure 2.8: Conceptual Architecture

Applying classification to clinical narrative texts this data we get the clusters shown in figure 2.8 above. Clearly the clusters obtained in this figure are better separated.

2.10 Chapter Summary

In this chapter we reviewed the pertinent literature related to our study problem as defined in chapter one. Through the review, we established the key concepts and theories involved in narrative texts. Computational techniques for addressing the identified problem: text classification and visualization were presented and discussed. We then went into the details of the deep learning algorithms and layer normalization techniques to address the problem of covariate shift. The theories of cognitive load theory, cluster hypothesis, data normalization techniques and information visualization theories were presented. A survey of related work was discussed and the gaps identified. To address the challenges experienced in using electronic clinical narrative texts, this study proposed a novel approach based on text classification and visualization. These ideas are well-founded in theory described in section 2.9's theoretical framework. Furthermore, the study presents a simple and effective method for supporting information retrieval from clinical narrative texts using SOAP documentation features which can be used to classify narrative texts into SOAP documentation format classes and then mapped to a visual graphical cluster map. Previous approaches to address the same problem have relied on the concept of timeline which is inadequate for modelling the multi-faceted nature of clinical narrative texts.

CHAPTER THREE: RESEARCH METHODOLOGY

In this section, we provide a summary of research methodology, research method and research design used to achieve the research goals and answer the research questions in Sections 1.4 and 1.5; respectively. We first provide an overview of the research process, followed by a summary of our research design. Finally, we discuss data analysis and interpretation and evaluation methodology.

3.1 Research Methodology

The two syllables “re” and “search” together make up the word "research. “Re” is a prefix that indicates again, and the verb search implies to look into or explore. Combining the two syllables make up the word ‘research’ that describes a thorough, methodical, careful study and inquiry conducted in order to establish facts or principles (Goundar., 2012). According to Rajasekar et al. (2006), research is the systematic quest for new information on a particular subject. Through objective and methodical analysis, it seeks to find solutions to scientific and social issues. A research methodology is a description of how a specific type of study is conducted. A problem can be solved systematically using a research methodology. It is a general term used to describe the processes researchers use to carry out research. Its goal is to provide the research work plan. The methods used for collecting and analyzing data are described in the research methodology. Data collection techniques are used to enable a thorough and in-depth understanding of a phenomena being examined from many perspectives and stakeholder lenses (Saunders et al., 2019; Bryman, 2016).

3.1.1 Mixed Methods Research Methodology

This section explains the methods used in this research, which included a study design that combined quantitative and qualitative techniques, a technique known as mixed methods research methodology. Research using mixed approach involved gathering both qualitative and quantitative data, combining them, and employing various designs that may include philosophical presumptions and theoretical frameworks. The fundamental tenet of this kind of study is that combining qualitative and quantitative methodologies results in a more thorough understanding of a research subject than utilizing one method alone (Saunders et al, 2019; Almeida et al., 2017; Creswell & Clark, 2017). A mixed research methodology was employed in this study. Qualitative approach was used to describe challenges encountered by physicians is using clinical narrative texts, the information needs of the physicians and the requirements of the proposed artefact. Descriptive survey research design complemented with lliterature review was adopted for informing the need of supporting information retrieval from clinical narrative texts in health care delivery setting. The findings from the descriptive survey design and literature survey were used to inform the development of the proposed model as per the overall research objective. The requirements were subsequently used to design an artefact that was used to classify and visualize clinical narrative texts. Following that, a quantitative approach was employed to evaluate the performance of the classification model and carry out user study of the final prototype. A user study was designed to evaluate the usability and utility of the developed artefact retrieval of information from clinical narrative texts.

3.2 Research approach

In this thesis we embraced the positivist research approach which relies on obtaining knowledge through observation and experimentation (Cohen, Manion and Morrison, 2007). This approach is particularly suitable with the deductive nature of research in machine learning models where a hypothesis is given and tested through a series of experiments. Various methods are used which include, but are not limited to, data representation schemes, model choice and optimization techniques (Ashfaq, 2019). The observations in the experiment are predictions often on a test dataset. The predictions are then compared to the ground truth to calculate an evaluation metric like accuracy, precision, recall. Finally, the evaluation metric is used for statistical inference and hypothesis testing. Although our research is primarily deductive, we also used to some extent exploratory and descriptive research methodologies. Since the clinical data in electronic health records poses a multitude of practical challenges, we adopted exploratory research methodology to establish the utility of the proposed artefact. Based on the findings of the exploration step, descriptive studies were used to understand and quantify the problem at hand in particular from a clinical perspective.

3.3 The Research Design

Kerlinger (1986) defines research design as a plan, structure, and strategy for gathering information in order to answer research questions or problems. It is a plan that provides a complete picture of how the researcher will conduct the research from start to finish (Kerlinger, 1986). To answer the research questions, this study followed experimental and expert intuition assessment approaches. The researcher introduced a qualitative study to describe the needs and requirements of physicians in seeking clinical information from clinical narrative texts. Descriptive survey research design complemented with lliterature review was adopted for informing the need of the solution to address the identified problem in using electronic clinical narrative texts. The findings from the descriptive survey design and literature survey were used to develop the artefact as per the overall research objective and were also adopted to answer RQ1, RQ2 and RQ3. The researcher adopted experimentation approach to answer research question RQ4. Evaluation using domain experts was adopted to answer RQ5.

Table 3.1: The relationship between research questions and research approaches

Research Question	Research Approach	Research Objectives
RQ1: What are the challenges physicians faces in using clinical narrative texts in electronic health records (EHRs)?	Survey from domain experts	RO.1
RQ2: What are the different types of clinical information we can infer in a corpus of clinical notes and how can we model them into visual information facets with their inherent relationships?	Literature review.	RO.2
RQ3: How can we build an artefact that supports information retrieval from clinical narrative texts?	Software development	RO.3
RQ4: Which deep learning technique can build an artefact's classification model for effective clinical text classification?	Experimentation	RO.4
RQ5: How well does the developed artefact solve the stated problem and meet the defined requirements?	Expert intuition	RO.5

Our methodology main idea was to classify a clinical narrative texts and displaying a visual output of the classified texts using a cluster map structure. This involves classifying clinical texts into predefined SOAP documentation format classes (Subjective, Objective, Assessment, and Plan) and personal identifying information (PII). The labeled texts are then grouped into semantically related clusters and displayed as a visual map. To achieve this, we approached the problem as both text classification and visualization problems where the clinical texts are classified by labelling them with predefined classes. The classified texts are then visualized using a cluster map. This is an important task which can help in the organization and retrieval of information from clinical text documents. We chose deep learning model to tackle text classification problem as inspired by the knowledge gained from the literature review about the recent state of art performance of convolutional neural networks in text classification tasks such as in (Gargiulo, Silvestri and Ciampi, 2018) and (Meng et al, 2018). We designed a series of experiments to evaluate the classification performance of the proposed classification model and comparing it with other baselines deep learning algorithms. For the visualization of electronic health data, the problems of protecting patient privacy and getting relevant information from the underlying text were investigated.

The developed artefact was evaluated with the intended users to assess its utility and its practical usability for its intended purpose in a healthcare delivery setting. The research sought to investigate the utility of the usability and utility of the artefact in helping doctors to retrieve information from clinical narrative text documents during care episodes. We hypothesized that classification and visualization of clinical narrative texts offers the potential to overcome information overload problem experienced in retrieving information in electronic clinical notes.

3.4 Research Method

There are two research paradigms that are used to characterize most of the research in Business & Information Systems Engineering (BISE); "the behavioural science paradigm and the design science paradigm" (Hevner et al., 2004). Design science focuses on creating new and innovative artefacts, while behavioural science is concerned with developing and testing hypotheses that explain or predict human or organizational behaviour (Hevner et al., 2004). In this thesis we adopted the Design Science Research Methodology (DSRM) proposed by (Peffers et al., 2006), a generic research framework for conducting design science research where artefacts are designed and built to solve real-world problems. The design science research methodology is a paradigm used to solve problems with the aim of enhancing human knowledge through the creation of innovative artefacts (Hevner and Chatterjee, 2015). An artefact in this case is a man-made product designed to address a particular problem (Hevner and Chatterjee., 2010). A construct, model, technique, instantiation, or an improved theory are some of the artefacts produced by DSR (Hevner et al., 2004), (Hevner and Chatterjee., 2004).

Design science research model has six phases which are follows:

i. Problem identification and motivation –The researcher specifies the research problem and justifies the benefits of the research.

ii. Objectives of solution- Stating the objectives of the research based on the problem specification. The objective solution can be either quantitative or qualitative. In qualitative solutions, the researcher develops a new artefact to solve the problem, while in quantitative solutions; the researcher finds better artefacts than existing ones.

iii. Design and development – The solution which address the problem is designed and the artefact is developed. The artefact could be a construct, a model, a method or an instantiation.

iv. Demonstration – The developed artefact is shown to the audience after the design and development stages to see how it supports the solution to the problem. This can be done using e.g., experimentation, case study, proof or simulation etc.

v. Evaluation – The artefact is evaluated against the problem specification. To explain variations from the artefact's intended behaviour, quantitative and qualitative methodologies could be applied.

vi. Communication – The researcher communicates the problem, the utility of the artefact and novelty, the rigors of the artefact design to the researchers and other relevant audiences.

This methodology revolves around having a problem that can be investigated by designing an artefact in order to solve it. The artefact is then evaluated in order to discuss and reflect upon whether or not the problem has been solved. This process model has been widely accepted by several academic disciplines as a research method (Weber, 2010). Examples include Computer Science (Preston & Mehandjiev 2004), engineering (Archer, 1984; Eekels & Roozenburg, 1991; Fulcher & Hills, 1996), (Takeda et al., 1990) and information systems (Hevner et al., 2004). Design science research methodology main objective is to create and evaluate artefacts that solve or help in identifying problems where no best practice exists. Our real-world problem in this thesis, was addressing the challenge of physicians in retrieving information from clinical narrative texts in electronic health records. This suited the nature of this research which makes design science the ideal choice.

This study adopted DSRM by Gjære, E.A. (2011) redrawn from the original Peffers' et al. (2006) DSRM to address the research objectives and the research questions. The research activities in this method are shown in figure 3.1 below. It outlines the six key stages of a research process, which have previously been characterized by DSR different process models. This process model is however different compared to other process models that lacked a standardized terminology, as well as proper distinction of where common activities take place. This process model also proposes four potential entrance points for research and specifies the type of research technique that will be acceptable when beginning at each of these entry points (Gjære., 2011).

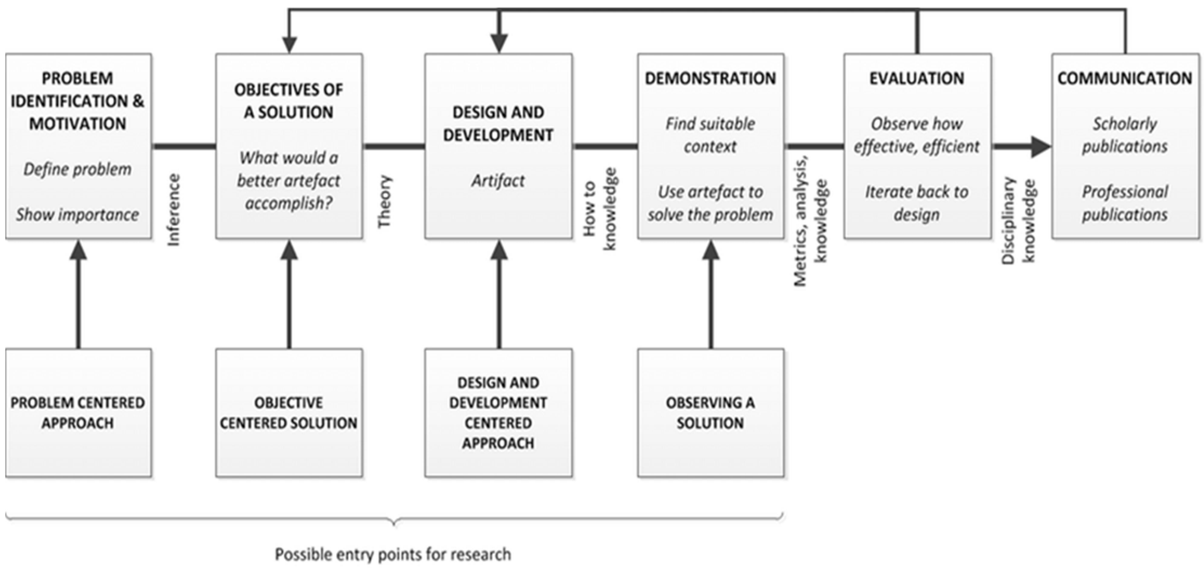

Figure 3.1: The design science research process (DSRP) model (Peffers et al., 2006): source: Gjære, E.A. (2011)

Table 3.2 shows an instance of the DSRP model used for this thesis' research showing how the tasks undertaken in this study map onto the overall research process model in figure 3.1 above.

Table 3.2: Instantiation of the DSRP model, with a problem centered approach

No.	Phase	Activities
1	Problem identification & Motivation	i. Need of automated technique to lessen cognitive load of physicians using clinical narrative texts. ii. Can text classification and visualization support physicians gain visual overview of clinical narrative texts, thus providing a dynamic account of a patient's clinical history?
2	Objectives of solution	i. Text classification and visualization model to support information retrieval from clinical narrative texts.
3	Design and development	i. Research on possible techniques in the literature. ii. Collect user requirements with throw-away prototypes and field studies iii. Build an artefact
4	Demonstration	i. Perform user studies using simulation with practical scenarios with the prototype. Discuss with intended users in focussed groups.
5	Evaluation	i. Evaluate results from user study results and users feedback (Questionnaires). ii. Perform experiments and evaluate the algorithm
6	Communication	i. Publish journal and conference papers ii. Write a Ph.D. thesis

In this thesis, we adopted problem centred approach. The details of the activities in the process model's different phases are described in detail below.

3.4.1 Problem identification and motivation

The problem identified in this thesis is the problem of information retrieval of the most relevant information in a potentially overwhelming long clinical narrative text documents in electronic form. The problem was identified using two techniques which are explained below;

3.4.1.1 Literature review

The study began with a critical literature review to understand the opportunities and challenges of electronic health records. Current information retrieval techniques were thoroughly reviewed to update the current landscape of information retrieval and identify current issues in the field. We reviewed a significant number of journal and conference papers which helped us identify the problem. We noticed there is a vast amount of related research works that are directly and indirectly related to our problem.

Clinical narrative texts such as clinical notes are important data type in medical practice. Most patient clinical records are in narrative text form which is both a challenge in processing and useful for clinical decision making. One of the challenges of clinical narrative texts such as clinical notes in EHRs is analysing large-scale medical documents. As a consequence, finding relevant information has become more difficult for physicians and several research works have also shown unique problems with existing computational approaches. The increasing use of electronic health records has benefited healthcare by providing access to a huge amount of patients' clinical health data. However, due to unstructured nature of this data, physicians are finding it increasingly difficult to locate the information of interest. Therefore, techniques for automated information retrieval from the enormous amount of clinical narrative documentation are urgently needed to overcome this challenge.

3.4.1.2 User survey

This study sought to better understand how doctors read and utilize clinical narrative texts in electronic health records. Our objectives were to understand the problems they encounter using electronic clinical texts and to understand how structuring and visualizing clinical text documents impacts text reading and to gain qualitative insights into physician information needs and preferences. Participants were asked about different types of information challenges encountered in retrieving information from clinical narrative text documents. Most of the challenges identified have been mentioned in the literature. Participants reported a number of challenges related to reviewing patients' clinical notes in electronic health records.

i. Availability of too much information in clinical narrative texts
ii. A lot of time spent reviewing patient clinical notes in electronic health records.
iii. Lack of cognitive support in retrieving information from electronic health records.
iv. Poor organization of clinical narrative texts.

Reviewing electronic clinical narrative texts faces significant challenges. Our findings support structuring and visual presentation of information in clinical notes to improve information retrieval tasks. There is need therefore to come up with new techniques to support physicians in retrieving information from clinical narrative texts.

3.4.2 Objectives of solution

The main objective of this research is to propose an artefact to support information retrieval from clinical narrative texts.

Other objectives are as follows;

i. To design a classification algorithm to select features that produce distinct facets of information.
ii. To design a visualization mechanism that provides support for exploring clinical textual documents.
iii. To develop an artefact based on the above techniques; text classification and visualization
iv. To evaluate the classification algorithm against state of art alternative designs.
v. To evaluate the usability and utility of the artefact with the target users.

The objectives of solution are directly related to our overall research objective in section 1.4.1 and to the four research objectives. RO1, RO2, RO3, RO4 and RO5 in section 1.4.2.

3.4.3 Design and development

In this thesis, a classification and visualization artefact was developed as per DSR methodology design and development phase (Peffers et al., 2006). The output of this research was an artefact for classifying and visualizing clinical narrative texts. It was developed, with the objective of addressing the current information retrieval problem which was identified in the problem identification phase. According to March et al, (1995), software artefacts can be classified into four categories namely; constructs, models, methods and instantiations. In this research, we developed an instantiation working artefact for classifying and visualizing clinical documents.

3.4.3.1 System development methodology

The artefact was developed using prototyping methodology where various prototype designs were exposed to users in order to get the approval and their feedback about design alternatives and options. This was repeated iteratively until the researcher received positive feedback from the users. In this thesis, classification and visualization techniques were applied on clinical text documents with the objective of supporting doctors retrieve relevant clinical information from clinical narrative texts. This can then facilitate clinical decision-making process in healthcare delivery by displaying a faceted visual presentation of long and complex clinical text on a single screen. In particular, the classification and visualization using a deep convolutional neural network and cluster map respectively were applied to patients' medical charts. The objective of the deep neural network used here is to take the input matrix of the clinical sentences, process it and classify it into any of the five semantic classes: Subjective, Objective, Assessment, Plan and personal identifying information. The details of the design and implementation are described in chapter four.

3.4.3.2 System development tools

We implemented the proposed deep learning algorithms using Python with Google TensorFlow, with the help of other scientific computing libraries: Numpy (van der Walt, Colbert and Varoquaux, 2011) and scikit-learn (Pedregosa et al, 2011). Numpy is the most complete scientific computation library available in Python; implementing most common methods from Linear Algebra, Statistics and provides n-dimensional arrays.

3.4.4 Demonstration

The developed artefact was exposed to the audience to evaluate how the solution solves the identified problem. We performed user studies using simulation with practical scenarios with the artefact. Evaluation was then carried out to establish how well the developed artefact solved the specified problem and how fully it met the requirements. We adopted the evaluation framework for evaluating visual data mining tools proposed by (Marghescu and Rajanen, 2004) to evaluate the usefulness of our visualization model by considering three levels of analysis:

i. Complete information – Evaluating to ascertain if the required information to make clinical decision is sufficient in the visual cluster map.
ii. Utility of the artefact- Evaluation of the utility of the artefact in providing useful information to help them to retrieve clinical information.
iii. Usability of the artefact- Evaluating the usability of the artefact on usability elements; ease of use, easy to learn, accurate, effective and efficient.

For each of the three levels, we identified and described the corresponding attributes.

Table 3.3: Three levels of analysis attributes

Usability	Ease of use Learnability Accuracy Efficiency
Information	Relevant information Accuracy Completeness Visibility Accessibility Satisfying Novelty
Utility	Richness Accuracy Clarity Understandability Fast Present ability Privacy Research

To get the end user perspective we used two sets of questionnaires; System Usability Scale (SUS) to evaluate the usability in relation to the visualization model and 7 Likert scale questionnaires to evaluate the information obtained from the artefact and the utility of the information obtained from the proposed artefact.

3.4.4.1 Selection of participants

To select study participants for both the survey and the questionnaire, we used a purposive sampling strategy. In qualitative research, targeted sampling is commonly used to identify and select information-rich cases related to the phenomenon of interest (Palinkas et al., 2015). Several inclusion and exclusion criteria were established during the process, as follows:

i. Survey - The survey's inclusion criteria required participants to be professional physicians with experience using electronic health systems in all healthcare settings.

ii. Individuals who did not meet the above inclusion criteria were excluded from the study.

Accordingly, fifty participants were selected to participate in the survey that provided in-depth expert information.

3.4.4.2 Data collection

In this study, we used a System Usability Scale (SUS) to collect usability ratings from users. We also administered a 7-Likert scale questionnaire to users to rate the information access and information usability of the visualization model. Both questionnaires were created online so that users could evaluate them. Follow-ups were conducted to ensure that respondents' responses to the study were high. Regarding the questionnaire used, there were two sections, namely Section A, which covered easy access to information, and Section B, which collected information about the usability of the information obtained from the visualization model.

3.4.4.3 Sampling Strategy and selection of participants

We used purposive sampling method to select study participants, for the evaluation of the visualization model questionnaire. To achieve this objective, inclusion and exclusion criteria were made as follows:

i. Questionnaire - The participants were required to be professional doctors with experience in using electronic health records.
ii. Doctors who did not meet the above criteria were exempted from the study.

Base on the above, fifty participants were selected to evaluate the developed prototype using questionnaire.

3.4.4.4 Pretesting the Instruments

Pretesting (or pilot testing) was used to determine the potential effectiveness of the questionnaire. This was done prior to administering the final questionnaire to the target population. Some physicians were sought out for advice and evaluation of the instrument from the initial draft to the final version. After this, the instruments underwent a pilot test in which they were given to experts in healthcare. They were asked to make insightful recommendations, particularly about the suitability, organization, and applicability of the study's questionnaires. They were also asked to evaluate the questions' clarity and how long it would take a respondent to answer each one. To increase the reliability of the instrument, their recommendations were included. The instrument was evaluated again a few individuals after corrections, and an improvement cycle based on their feedback then took place. The focus of this revision was strengthening the content's consistency and validity. Consistency examines if there is agreement between the instrument items and the idea, whereas content validity examines whether the instrument covers an acceptable content of the relevant domain issue to be examined.

3.4.4.5 Data Analysis

Statistical analysis techniques were used to test if the difference in performance between the different techniques that were used for learning was significant.

Two types of data analysis were carried out:

i. Descriptive statistical analysis
ii. Qualitative analysis.

This was applied to the analysis of the perceived effectiveness of the visualization model.

3.4.4.6 Reliability and Validity

Credibility of any research involves establishing that the results of research are credible or believable. During research, there are chances that wrong answer may be included in the sample, which could affect the results. In this thesis, we have tried to minimize the threats towards validity and reliability to our research.

3.4.4.6.1 Validity

Traditionally, validity is defined as “The degree to which a test measures what it claims, or purports, to be measuring” (Brown, 1996). In our study adopted both construct validity and content validity. Construct validity is “the degree to which the items on an instrument relate to the relevant theoretical construct” (Kane, 2001), (DeVon et al., 2007) whereas content validity refers to the degree to which a measure represents all attributes of a given construct (Parsian and AM, 2009). We used content validity to determine whether the content of the questionnaire was appropriate and relevant to our study objective. We used construct validity to ascertain how well our test measures what it was supposed to measure.

To achieve construct validity of our study, we partitioned the questionnaire into different sections with the aim of ensuring that each section assessed information for a specific objective. To achieve content validity, we sought the help of professional doctors to thoroughly examine the content of the questionnaire. They were asked to rate the statements in the questionnaire for relevance and meaningfulness and for achieving the intended purpose. The instrument was then adjusted based on the feedback to improve content validity before being used for actual data collection. The validity of the questionnaire was achieved by conducting a mini-pilot study in which it was tested with a professional physician experienced in the use of clinical documentation prior to its actual use for further refinement. During the interviews, the researcher summarized the interviewee's answer for each interview question and presented it to the interviewee for immediate correction(s). For the study questionnaire to measure what it needs to measure; Pilot tests are carried out before the study questionnaire is used for actual data collection. Fifteen respondents who participated in the study were given a sample questionnaire, which was then checked for completeness, ambiguity, and language. Necessary adjustments were made before the actual data collection.

3.4.4.6.2 Reliability

The reliability of internal consistency is the most commonly used psychometric measure to evaluate survey instruments and scales. (Twycross and Shields, 2004) defines reliability as the consistency, stability and repeatability of results, i.e. a researcher's result is considered reliable when consistent results have been obtained in identical situations but different circumstances. We analysed our questionnaire for overall reliability and internal consistency. To check the reliability of our scales used in our questionnaire, Cronbach's alpha coefficient was used and it is defined as “a measure used to assess the reliability or internal consistency of a set of scales or test items”, i.e. the reliability of a given measurement relates to the extent it shows consistency of a concept, and this achieved using Cronbach's alpha. It’s commonly used to assess the internal consistency of a questionnaire (or survey) composed of multiple Likert-type scales and items. Cronbach's alpha test is commonly used to assess questionnaire respondent consistency (Mitchell and Jolley, 2012) and provides an estimate of reliability based on indicator correlations (Henseler et al., 2009). According to Mitchell and Jolley (2012), alpha coefficient values above 0.70 are considered acceptable. Cronbach's alpha reliability coefficient is usually between 0 and 1, but according to Gliem and Gliem (2003) there really is no lower limit. The closer Cronbach's alpha coefficient is to 1.0, the greater the internal consistency of the items in the scale (Gliem and Gliem 2003).

Cronbach's alpha α is a coefficient of internal consistency is used as an estimate of reliability. Internal consistency measures the correlations between different items in the same test. Internal consistency measures whether multiple items proposing to assess the same general construct yield similar scores. Cronbach's alpha α is calculated by correlating the score for each scale item with the total score for each observation (usually individual survey-takers or test-takers) and then comparing it to the variance for all individual item values:

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} \sigma_{y_i}^2}{\sigma_x^2}\right)$$

Where: k refers to the number of scale items

σ2yi refers to the variance associated with item i σ2x refers to the variance associated with the observed total scores

Sprole and Kendall (1986) provide the following rules of thumb for interpreting different values of Cronbach alpha coefficient.

Table 3.3: Test Analysis: Standard Measurement of Internal Consistency of the Factors

Cronbach's Alpha(*α)*	Internal Consistency and Reliability
Alpha >0.70	Excellent
Alpha>0.40	Good
Alpha<0.40	Poor
Alpha=0	Unacceptable (no relation)

3.4.5 Evaluation

This section discusses the various experiments that were carried out to evaluate different classification models used in the proposed model. We evaluated different deep learning algorithms, on semi synthetic data sets to determine the most suitable approach for clinical sentences classification. Patient medical text charts were classified into the following categories: Subjective, Objective, Assessment, Plan and personal identifying information. We constructed features from clinical charts using word and sentence embedding.

To evaluate the performance of the classifier; we conducted a series of experiments while comparing the proposed model performance against the baseline's models. All the algorithms were implemented using Scikit-learn, a machine learning package in Python. Various classification algorithms were implemented to predict the semantic classes of the various clinical sentences/expressions which appears in a given a clinical document (patient medical chart). The evaluation of the proposed classification model performance was made using three aspects:

i. Cross Entropy loss (The speed of convergence of training model)
ii. The accuracy of text classification for untrained text input;

3.4.5.1 Cross Entropy loss

A type of loss function that is very often used in classification tasks with neural networks is the cross-entropy loss. The cross-entropy loss measures the performance of a classification model whose output is a probability value between 0 and 1. The cross-entropy loss increases when the predicted probability differs from the actual label.

In binary classification, where the number of classes C equals 2, cross-entropy can be calculated as:

$$Entropy = (ylog(p) + (1 - y)log(1 - p))$$

If C>2

(i.e., multi-class classification), we calculate a separate loss for each class label per observation and sum the result as shown below.

$$Entropy = -\sum_{c=1}^{M} y_i \text{, c } \log(p_{i,} c)$$

Where y_i

C - Number of classes (Subjective, Objective, Assessment, PII)

log - the natural log

y - Binary indicator (0 or 1) if class label c is the correct classification for observation i - i is of class c

p - Predicted probability observation

The former can be measured by the number of the epochs required to reach the relevant classification accuracy for training data. To demonstrate the performance of the proposed model, we compared the cross-entropy loss with other three baselines:

i. Convolutional Neural Network
ii. Convolutional Neural Network with ResNet
iii. CNN ResNet with Range normalization

We also introduced the use range of normalization on CNN with residual connections in order to established the effect of range normalization on the cross entropy on various baseline models.

3.4.5.2 Classification Accuracy

The accuracy measures the accuracy in classifying the untrained clinical text into relevant semantic classes.

$$Accuracy(ACC) = \frac{\Sigma\text{TP} + \Sigma\text{TN}}{\Sigma\text{TP} + \Sigma\text{TN} + \Sigma\text{FP} + \Sigma\text{ FN}}$$

Where

TP -True Positives

TN- True Negatives

FP- False positives

FN-False negatives

To demonstrate the performance of the proposed model, we compared its performance against the following above three baselines.

An experimental approach was adopted in this research because it allows a researcher to experiment and compare several alternatives. It is widely accepted that experiments are useful in demonstrating cause and effect and showing outcomes when variables are controlled or manipulated.

Table 3.4: Baseline models and proposed model

Description	Deep learning model	Description
Baseline	CNN	In this experiment, sentence embeddings with a convolutional neural network is used.
Alternative 1	CNN with Range Normalization	In this experiment, sentence embeddings with convolutional neural network is used. After each convolutional layer the range normalization is applied this map the data to a desired range (ex. [0, 1] in our case) through a simple linear transformation.
Alternative 2	CNN ResNets	In this experiment, A CNN with residual, skip connections is used.
Alternative 3	CNN ResNet with Batch Normalization	A CNN with residual, skip connections with Batch Normalization.
Proposed model	CNN ResNet with Range Normalization	A CNN with residual, skip connections with Range Normalization.

3.4.5.3 Range Normalization versus Batch Normalization

It has been demonstrated that deep neural network training is challenging. Due to the issues of overfitting, vanishing gradient, and covariate shift, deepening a neural network frequently makes it more challenging to train. In this thesis we proposed the use of range normalization to help overcome the above problems. In this experiment, we compared the performance of range normalization against batch normalization which is our baseline model. The two architectures are shown below.

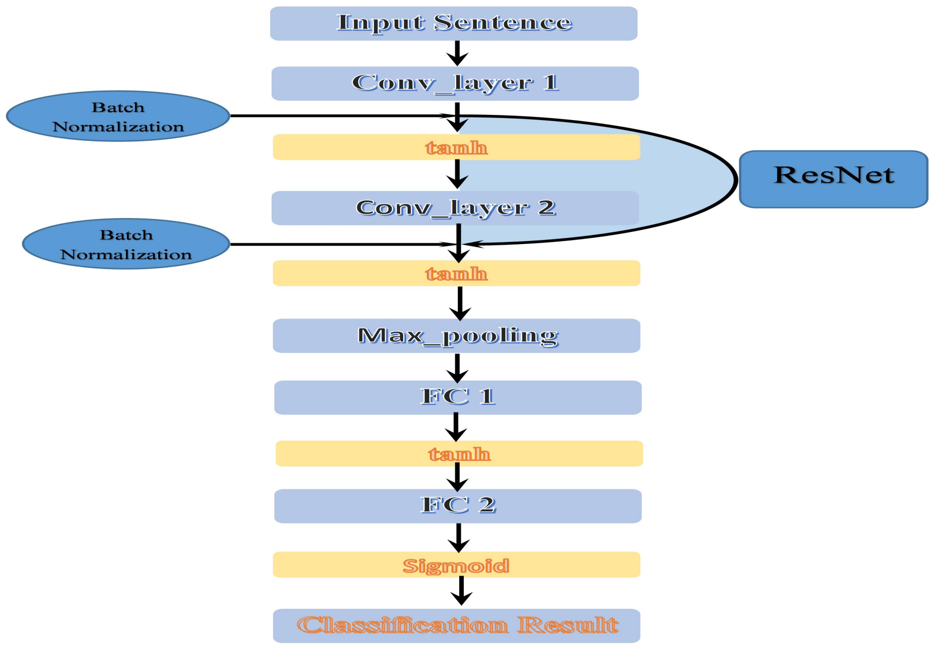

Figure 3.2: Batch Normalization

This layer is applied on the output of the convolution layer and computes a normalized array $Y = Batch_{\Gamma,\beta}(X)$ where

$$Y_{i,k} = \Gamma_k \hat{X}_{i,k} + \beta_k$$

Γ_k and β_k are parameters of batch normalization for specific feature k and $\hat{X}_{i,k}$ is the normalized value of $X_{i,k}$ with respect to the mean and variances of feature values in batch $\mathcal{B}$:

$$\hat{X}_{i,k} = \frac{X_{i,k} - E_{\mathcal{B}}(X_{.,k})}{\sqrt{Var_{\mathcal{B}}(X_{.,k})}}$$

$E_{\mathcal{B}}(X_{.,k})$ and $Var_{\mathcal{B}}(X_{.,k})$ respectively denote the average and variance of feature k in terms of batch $\mathcal{B}$:

$$E_{\mathcal{B}}(X_{.,k}) = \sum_{i=1}^{n-m+1} \sum_{X \in \mathcal{B}} X_{i,k}$$

Range normalization layer

This layer is applied on the output of the convolution layer and where a function is used map the data in a desired range (ex. [0, 1] for this case) through a simple linear transformation. Assume there are n numbers x_i (i=1, 2, …, n) which have to be mapped in a range [0, 1]. Then the result y_i (i=1, 2, …, n) can be obtain using the following equation:

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}},$$

where $x_{\min}$ is the minimum value of x_i and $x_{\max}$ is the maximum value. Because this is, of course, the linear function, the minimum value of y_i is obtained when x_i is equal to $x_{\min}$ and so is the maximum value of y_i. If we substitute the $x_{\min}$ into x_i, we obtain $y_{\min} = 0$. Similarly, we also obtain $y_{\max} = 1$. The new numbers y_i will be therefore distributed in the range [0, 1] as desired. Note that there may exist the special case, $x_{\min} = x_{\max}$, which means all the values of x_i are the same ($x_i \equiv x_{\max}$). In this case, the denominator of the above equation is equal to 0, which yields "the division by zero." No problem! We can set y_i's to 0.5. The range normalization is very simple to be implemented and does not increase the complexity of the CNN.

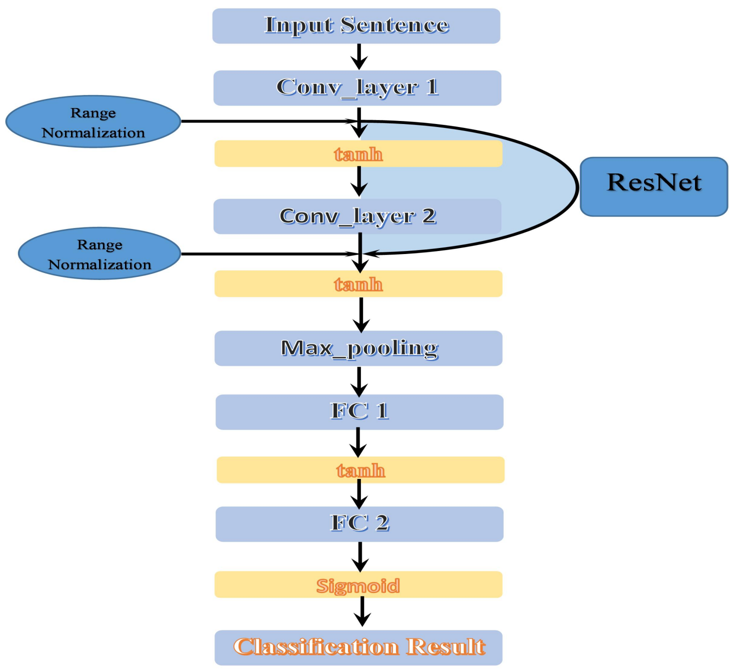

Figure 3.3: Range Normalization

To evaluate the performance of the two normalization techniques, we conducted a series of experiments while comparing cross entropy and classification accuracies for the two techniques.

3.4.5.4 Clinical Datasets

Although physicians use a wide variety of clinical documents, we have focused on one commonly used document, the patient medical chart, because of its common use in clinical care. We will use clinical notes that describe a patient's medical history. In this study, we used the patient record as our source of clinical documents. For evaluation purpose, we used a dataset of 50,000 semi-synthetic medical documents developed from an original set of clinical documents obtained from I2B2. They were then customized to fit the local context with the help of a professional doctor who has experience using electronic health records. These reports were chosen to support training and testing for the proposed model. The reason why we were unable to get real live patient data was because of privacy and confidentiality concerns which limit third party access to patients' data. In our thesis, this is one of the problems we have tried to address. Each record consists of a chart covering patient records varying in duration from a few months to 5 years. The charts covered a wide range of common tropical ailments from malaria and respiratory infections to diabetes and urinary tract infections

3.4.5.5 Validity of the classification model

Cross-validation is commonly used to assess the accuracy and validity of a machine learning model. K-fold cross-validation is often used to perform multiple assessments on different test sets before combining the results of those assessments. The original corpus is divided into K subsets called folds. A valid model should have good prediction accuracy. Data is often split into training and validation/test sets. The training set is used to train the model and the validation/test set is used to validate it against data it has never seen before. In our case, we used a stratified sample 10-fold cross-validation to create a balanced distribution in each fold. In k-fold cross-validation, the original sample is randomly divided into k sub-samples of equal size. From the k subsamples, a single subsample is retained as validation data to test the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times, using each of the k subsamples as validation data exactly once. The k results can then be averaged to produce a single estimate.

3.4.6 Communication

In this this stage, we published a number of international journal and conference papers related to our approach. The entire research process is also documented in the thesis.

3.5 Chapter summary

In this chapter, we discussed the research methodology followed in order to address the identified research problem. We described the artefact design, implementation and evaluation. Research validity and reliability, were also discussed. In summary, the methodology of the study was systematically designed, with each research objective linked to a specific research question, the research design, and the expected results. The details are presented in table 3.4 below.

Table 3.4: Summary of the research methodology

Research Question	Research Objectives	Research Methodology	Expected outcomes
To investigate the challenges that physicians face in using clinical narrative texts in electronic health records (EHRs).	What are the challenges physicians faces in using clinical narrative texts in electronic health records (EHRs)?	User survey from domain experts Literature review.	A comprehensive understanding of the challenges encountered in using clinical narrative texts
To investigate different types of clinical information we can infer in a corpus of clinical notes and how to model them into information facets with their inherent relationships.	What are the different types of clinical information we can infer in a corpus of clinical notes and how can we model them into visual information facets with their inherent relationships?	Literature review.	A taxonomy of information facets that makes up a clinical chart.
To design and implement classification and visualization artefact to support information retrieval from clinical narrative texts.	How can we build an artefact that supports information retrieval from clinical narrative texts?	Software development	A software artefact for classifying and visualizing clinical texts
To evaluate the proposed artefact' s classification model performance against other deep learning baseline models.	Which deep learning technique can build an artefact's classification model for effective clinical text classification?	Experimentation	Best classification model in terms of cross entropy loss and classification accuracy
To evaluate how well the artefact solves the stated problem and meet the defined requirements	How well does the developed artefact solve the stated problem and meet the defined requirements?	Expert intuition	Usability evaluation of the developed artefact by the intended users . The utility, quality, and efficacy of the design artefact

CHAPTER FOUR: DESIGN AND DEVELOPMENT OF THE ARTEFACT

In this chapter, we discussed the applications of text classification and visualization techniques for the design of an information retrieval support artefact for clinical narrative texts. In particular, we apply deep learning methods for the classification of different categories of narrative texts involved in clinical documentation. Two types of layer normalization techniques, batch normalization and range normalization, are investigated. Issues of covariate shift, vanishing gradients and retrieval clinical narrative texts granulation are studied in detail. We began by giving a general overview of our design. Evolutionary prototyping methodology which was adopted is then discussed. This is followed by a section that lists the requirements of the artefact. The system design section that follows describes how the system was set up to satisfy the requirements.

4.1 Evolutionary Prototyping Design

In this thesis, we used an evolutionary prototyping approach to create an artefact to solve the identified problem. Several software development techniques are grouped under evolutionary process models, including evolutionary prototyping (Aggarwal & Singh, 2008). These can be employed in projects that make use of novel technology which is not fully understood and documented. They are also useful in instances where the project's system requirements may not have been completely clear. The following are some of the instances under which evolutionary prototyping can be used as the software development process, according to Aggarwal & Singh (2008):

i. System requirements are not well defined and understood
ii. Instances where requirements frequently change
iii. Instances where system requirements represent a complex system is to be developed
iv. Instances where the development team has less experience developing similar systems
v. Instances where the team has less domain knowledge and
vi. Instance where the team has less experience on the tools to be used

A throwaway prototype or an evolutionary prototype may be the outcome of the prototyping process (Ghezzi et al., 2003). The purpose of the throwaway prototype is to clarify requirements so that the system specification document may be prepared (Sommerville, 1992). On the other hand, the evolutionary prototype gradually develops into the finished product (Ghezzi et al., 2003). Sommerville (1992) points at artificial intelligence (AI) systems as examples of systems that may be difficult to specify from the beginning. According to Ghezzi et al. (2003), developers usually have only a vague idea of how AI systems are going to work.

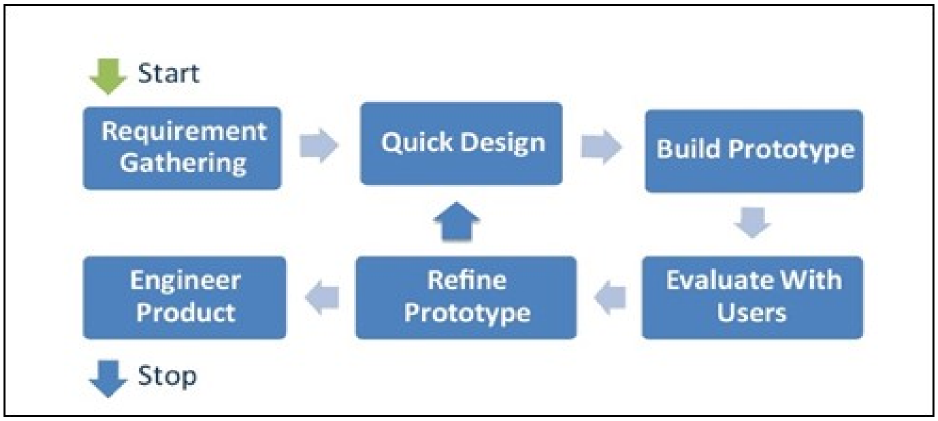

Figure 4.1: Evolutionary prototyping model: source (Kris, 2022)

4.2 Requirements for artefact

To collect the requirements for the artefact a user survey was conducted. A survey, allowed us to collect requirements from many participants within a relatively short time. This was especially helpful since the participants were spread out geographically and their input was needed to help establish artefact requirements. We adopted purposive sampling strategy to select the participants. In qualitative research, targeted sampling is commonly used to identify and select information-rich cases related to the phenomenon of interest (Palinkas et al., 2015). Inclusion and exclusion criteria were established during the process, as follows:

i. Survey - The survey's inclusion criteria required participants to be professional physicians with experience using electronic health systems in all healthcare settings.

ii. Individuals who did not meet the above inclusion criteria were excluded from the study.

Accordingly, five participants were selected to participate in the survey that provided in-depth expert information. In addition literature review was used to compliment the survey process. From the survey and the literature, it was found out that physicians always have a limited amount of time to review and use patients' medical histories which is the primary source of patient history clinical information. Also, most current electronic health records that have been adopted in the last few years do not provide strong support for information retrieval from clinical narrative texts. The first step in obtaining information from a clinical document is to identify important key information of a particular patient that may be useful to handling a case at hand. To determine the information needs of physicians, we conducted a study of the information needs of physicians during healthcare to determine the types of data that meet their information requirements. During the study, the information needs of physicians in both inpatient and outpatient settings were identified and classified. Our study showed that physicians depend on patients' medical records to provide insight into a patient's medical history and provide important details that help physicians make informed clinical decisions. It contains different types of information such as Subjective, Objective, Assessment, and Plan which reflect different aspects of a patient. Results demonstrated the need to organize and present classes of clinical data that could meet physicians' information needs without overwhelming them with irrelevant information. Therefore, there is need to identify and classify the various types of information, which are elements within clinical narrative text that fall within predefined semantic classes. The clinical sentences or expressions that need to be classified fall in one of five categories – Subjective, Objective, Assessment, Plan and personal identifying information.

The goal of the developed artefact was to help physicians get a visual summary of a patient clinical history by identifying useful information in clinical narrative texts with various information facets. The objective of the artefact is to support an overview of clinical narrative texts and information retrieval. It allows the physician can look at higher level facets on information and then dig deeper and identify the specific information in various semantic facets. Given the information gathered from the survey and in the literature, and the objectives of the study, functional and non-functional requirements were formulated.

4.2.1 Functional requirements

i. To classify and organize clinical sentences in form of clusters in a way that indicates their contents and specifies any relationships to other clusters. The five requirements of our classification and visualization model include:
ii. A visual cluster display that shows distinctive, human-readable name that gives an indication of the content of the cluster (clinical sentences).
iii. A visual display that that organizes clinical sentences into semantic classes (where necessary) and displays them uses a consistent pattern.
iv. There should be no repetition of semantic elements among the semantic clusters.

4.2.2 Non-functional requirements

The non-functional requirements of the proposed model were identified as usability, reliability, performance, and compliance with patient privacy requirements.

4.3 Modelling SOAP clinical notes

It is common for physicians during clinical encounters with patients to be concerned with past clinical aspects of a patient – such as symptoms, diagnosis and treatments over time. In this thesis we sought to classify and visualize these aspects of concern and form a cluster map. This involved classifying clinical texts into various categories in order to generate clusters of information that are then displayed as a cluster map. In this thesis we based our classification and visualization on S.O.A.P documentation format. S.O.A.P documentation format is a framework used by physicians to organize and interpret clinical documents (Mowery et al, 2012). It is useful in organizing clinical information in a way that supports assessment, reasoning, and decision making (Weed, 1971). For each patient, documentation during patient encounter, the physician writes four kinds of information (S) subjective, (O) objective, (A) assessment and (P) plan. The descriptions are described in the below:

i. Subjective(S) – The clinician begins by documenting symptoms to understand the patient's clinical state (S).
ii. Objective (O) - The clinician records signs, quantifiable data and scientific evidence experienced by the patient (O) to come up with diagnosis.
iii. Assessment (A) - The clinician unifies and critically evaluates subjective and objective information to make a conclusion e.g. a disease or a condition.
iv. Plan (P) - The physician formulates the care plan to treat the underlying condition or disease.

To classify and visualize texts in clinical narrative texts, this framework uses four SOAP (Subjective, Objective, Assessment and Plan) documentation format elements. In addition we included fifth information element-Personal identifying information (PII). The framework structures a clinical narrative text into distinct facets pieces of information as well as displaying the visual output. SOAP documentation format is widely accepted and used as an important framework to guide physicians in developing a holistic documentation of patients' records and promoting organization of clinical narrative texts. Thus we based our modeling on SOAP documentation format. SOAP documentation format, helped us modelled clinical narrative texts into distinct information facets.

4.4 Overview of the proposed design

We present a classification and visualization artefact for clinical documents, a novel technique for supporting retrieval of information from clinical narrative texts. An artefact is designed where narrative texts are placed and accessed in groups called clusters. All texts in a cluster discuss a common subject. This establishes a logical structure for narrative texts to facilitate information retrieval. By structuring texts into clusters, complete patient information is stored in one location and the information retrieval overhead is reduced. Usually, long documents can be cognitively difficult to review. It is therefore important to create a system that classify information into various categories, and visually display the information so that users can see multi-faceted view of records. The artefact supports information retrieval from clinical narratives in two phases: locating labelled cluster and reading its content. Thus, when clinical narratives are structured into labelled clusters, physicians can easily retrieve information better than in a large document. The design principle of this artefact is to support information seeking by incorporating text classification with visual display of classified texts. We envisioned the proposed artefact as a tool that supports quick retrieval of clinical information from clinical narrative texts, with the potential of reducing cognitive overload and providing a doctor with a visual summary of a patient's clinical history.

More specifically the design objectives are;

i. To automatically read a clinical document and assign an appropriate class label to individual sentences
ii. To map labelled sentences to predefined information clusters.
iii. To visually display clusters of sentences using a visual cluster map
iv. To support information retrieval tasks by offering selective reading of individual clusters of information in the visual map.

4.4.1 Clinical text classification

We built a deep convolutional neural network and trained on few thousand medical charts to build a classification model. The model classifies clinical sentences into four SOAP classes and personal identifying information (PII). We based our classification on SOAP documentation format because it is the mostly used format. Our task is to classify each clinical narrative text document into four categories or a fifth category indicating personal identifying information (PII). To achieve this, we implemented a deep learning algorithm using Python with Google TensorFlow, with the help of other scientific computing libraries:

Numpy (van der Walt, Colbert and Varoquaux, 2011) and scikit-learn (Pedregosa et al, 2011). Numpy is the most complete scientific computation library available in Python; implementing most common methods from Linear Algebra, Statistics and provides n-dimensional array. We used the generic Subjective, Objective, Assessment and Plan SOAP sections and PII as our class labels. We build a classifier that classifies information in a medical chart into the above classes.

Given a string of words S, determine whether S expresses Subjective, Objective, Assessment, Plan or Personal Identifying Information. Let's formally define the variables that will be used in the proposed classification model.

We have two sets of variables

1. **Sentences:** $S = \{s_{1,} s_{2,} \ldots \ldots \ldots s_n\}$ where n is the number of sentences in the document. s_i denotes ith sentence in the set *S. Note — Sentence here a string of words or figures .*
2. **Semantic classes:** $\mathbf{C} = \{\mathbf{c_{1,}} \mathbf{c_{2,}} \ldots . \mathbf{c_n}\}$ – Semantic classes of various string of words. The number *n* is a parameter which specifies the number of classes. We formally redefined the clinical document classification problem as follows:

Given a clinical document with a set of clinical sentences, $S = \{s_{1,} s_{2,} \ldots \ldots \ldots s_n\}$ and a set of classes, $C = \{c_{1,} \ldots \ldots . . c_n\}$ and class assignments $C = \{s_{i,} y_{i,}\}$ where s_i denotes the i^{th} sentence and y_j means class of the i^{th} category with $y_i \subseteq C$ for all $1 \leq i \leq 5$.

More formally, we have a set *S* of sentences and a set *C* of classes. The goal is to find a function *f*::*S*→*C* such that *f* classifies s∈S to the correct *c*∈*C*. To achieve this goal, a supervised machine learning approach was adopted.

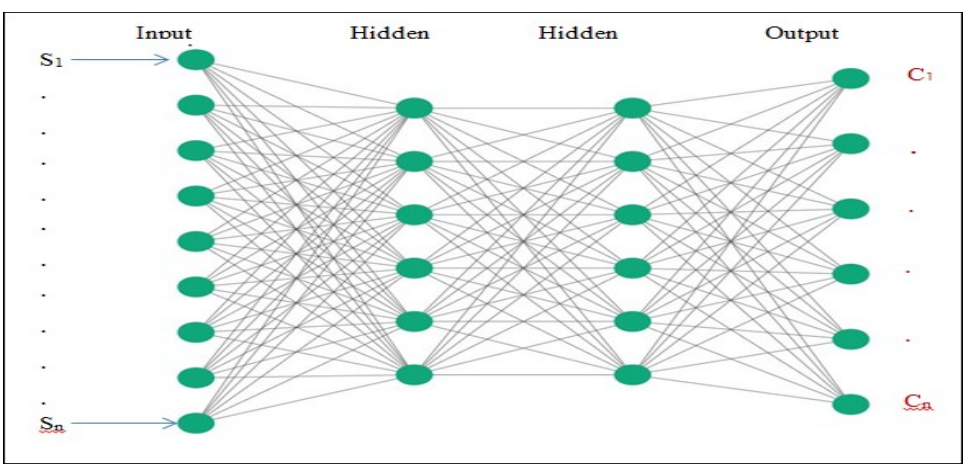

Figure. 4.2: A schematic diagram of a classifier

Formally, a text document is defined as D= $\{s_{1,}s_{2,}s_3 \ldots \ldots \ldots s_n\}$. Given a training set T = $T = \{(s_{1,}c_{1,}) \ldots \ldots (s_n, c_n)\}$, where c represents the label of the corresponding sentence, the objective is to learn a classifier that is able to predict a new class label of any new instance as accurately as possible. The figures 4.3 and 4.4 below demonstrate this.

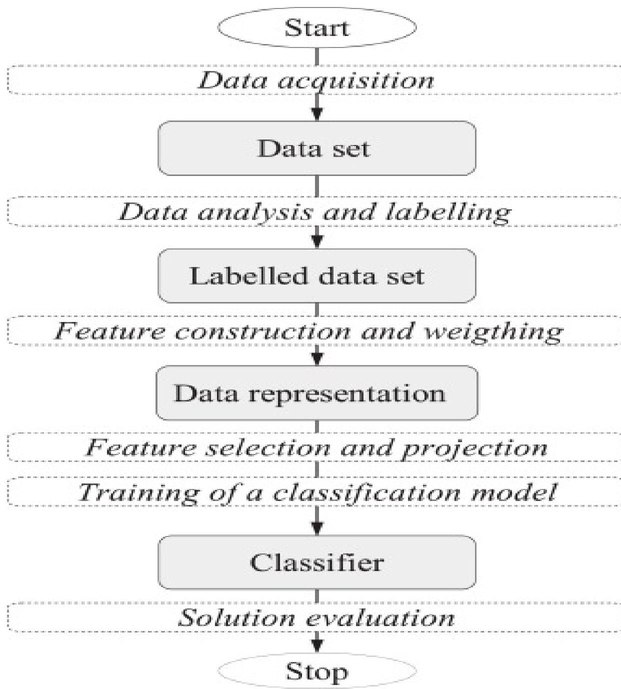

Figure. 4.3. Flowchart of the text classification: source (Mirończuk and Protasiewicz, 2018)

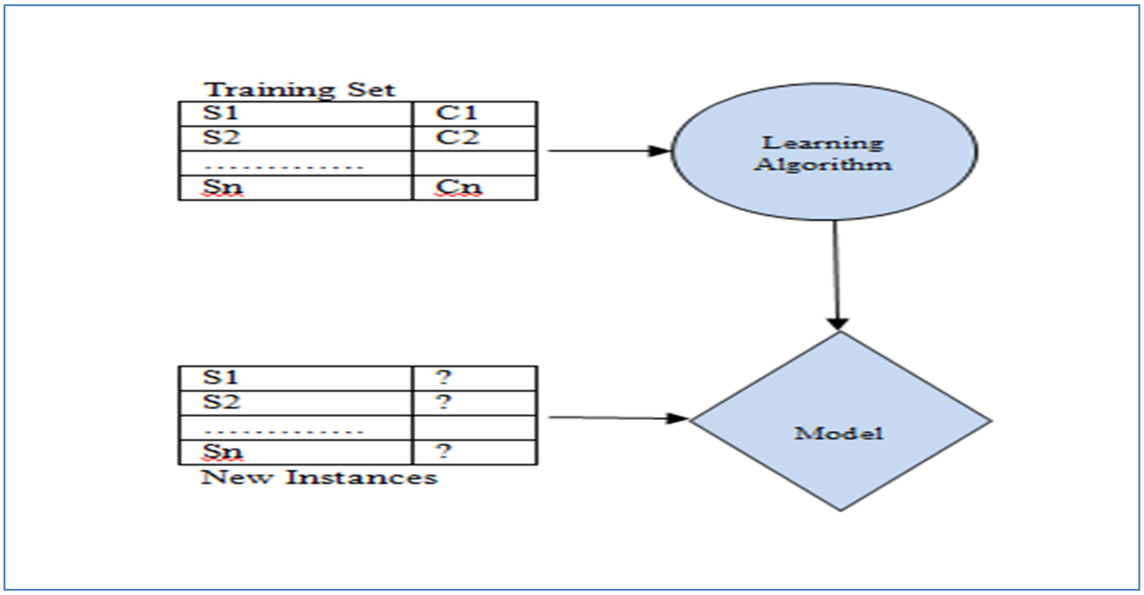

Figure 4.4: Classification model: source(author)

Now we set up a simple neural net with 5 output nodes, one output node for each possible class. We can generalize as follows, given a dataset of pairs *(sj , cj)* where sj is a clinical sentence of one or more words and cj is one of the possible classes for the clinical sentence i.e. cj = {Subjective, Objective, Assessment, Plan and Personal identifying information (PII)}. Our objective is to design a function or a classifier F which maps an arbitrary sentence to one of the five possible classes.

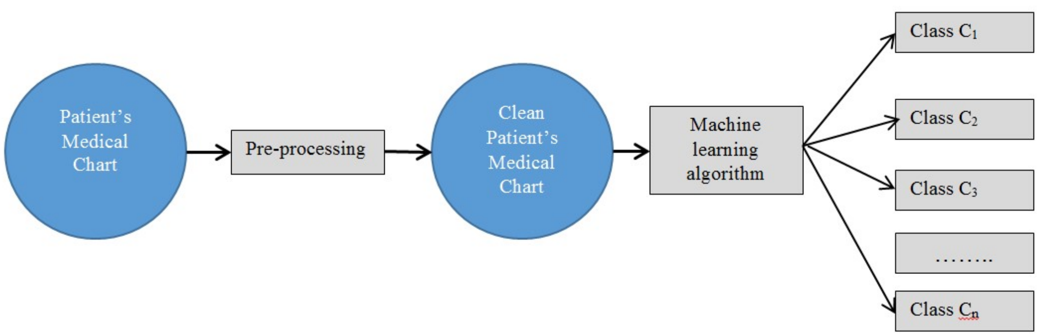

Figure 4.5: Classification process flow

Table 4.1- Sample classified sentences

Clinical Sentence	Semantic Classification
High fever	Subjective
Fatigue	Subjective
Frequent urination	Subjective

Frequent infections	Subjective
Pressure: 113/79 mmHg	Objective
Temperature:37	Objective
Heart Rate: 57 bpm	Objective

4.4.2 Visualization of classified sentences using a cluster map

A cluster map is generated by combining two stages; grouping similarly labeled texts obtained from the classification phase into one cluster and then joining them with their default relationships into one cluster map. It allows one to see, at a glance, the different aspects of the narrative text, thus helping identifying a particular aspect to focus on to get information. This aapproach is taken to represent a patient clinical narrative text in form of a visual cluster map that conceptualizes information space in terms of possible information facets and their relationships.

Given a clinical document *D* our goal is to build a cluster map where each cluster $\mathbf{C}_i \ldots \boldsymbol{C}_n$ contains a set of semantically related clinical sentences/expressions. There is an edge from cluster $\boldsymbol{C}_i$ to cluster $\boldsymbol{C}_{i+1}$ if a cluster $\boldsymbol{C}_i$ *has* some relationship with cluster $\mathbf{C}_{\mathrm{i}+1}$. We applied a cluster map to arrange sentences in terms of semantic classes as a means of analysing the multi-faceted information in a patient medical chart. A graph is a structure formed by a set nodes and a set of connections between pairs of nodes. We defined a cluster map as a heterogeneous graph $\mathbf{C}_i \ldots \boldsymbol{C}_n$ where $C = \{\mathbf{c}_{1,} \ldots, \boldsymbol{c_n}\}$ is a set of all semantic classes (clusters) and $L = \{\mathbf{l}_{1,} \ldots, \boldsymbol{l_n}\}$ is a set of all links between classes. Each class $\mathbf{c}_{i,} \in$ C has a semantic type and a set of sentences associated with it, denoted by $T(\boldsymbol{c}_{i,})$ and $(\mathbf{c}_i) = \{\boldsymbol{s_1}(\mathbf{c}_{i,}) \ldots, \boldsymbol{s_n}(\boldsymbol{c_i})\}$ respectively. Note that the number of sentences may vary for different types of classes. Every class $\mathbf{c}_{i,} \subset$ C is a semantic aggregation of sentences of the same type. This is illustrated in the figure 4.6 below.

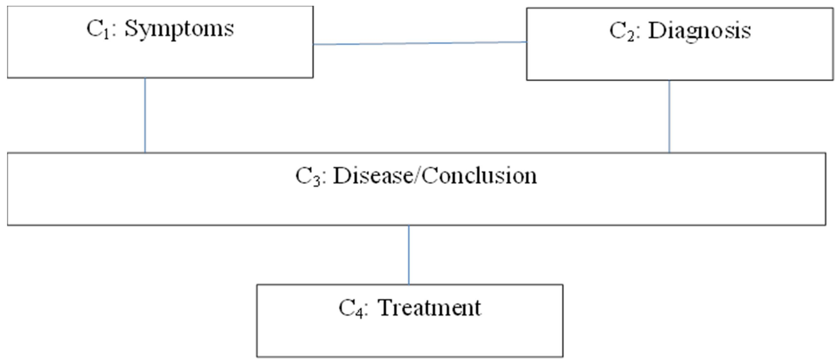

Figure 4.6: Clinical cluster map

Our cluster map is a graphic or pictorial arrangement of key concepts related to a patient's clinical history. By presenting clinical information as a cluster map, users can be able to visualize various aspects of a patient's care relate to each other. Clinical documents can be typically represented by four clinical concepts: Subjective, Objective, Assessment and Plans (SOAP). Classifying sentences into these categories can benefit many other text-analysis tasks. Although few studies such as (Mowery et al., 2014), have applied different approaches for automatically classifying sentences in clinical notes into the SOAP categories, few have explored the classification and visualization of sentences that appear in clinical notes.

We believe that, this model can make positive contributions towards helping physicians easily understand the course of a patient's care episode as described in a clinical document (patient's medical text chart) by facilitating accurate interpretation and understanding of events in the patient's medical text chart.

The outputs (labels) are Subjective, Objective, Assessment, Plan and personal identifying information. For example, the clinical text for <u>symptoms</u> will be "Extreme hunger, frequent infections, unexplained weight loss, increased thirst, frequent urination, irritability, slow-healing sores, fatigue, blurred vision", which consists of many word-combinations that are separated by comma and have to be classified as symptoms, accordingly. In this case, the clinical text is made of 4 words or less. And for <u>diagnosis</u>, the clinical text will be "Auto-antibodies detected in blood. Patient had a A1C level of 7.0. Ketones detected in urine.", and each sentence is separated by "." has to be classified as diagnosis, accordingly. So is the clinical text for <u>treatment</u> such as "Patient advised to cut weight. Regular monitoring of sugar levels prescribed. Patient advised to center their diet on more fruits, vegetables and whole grains and to cut down on animal products, refined carbohydrates and sweets. Participation in regular physical activities recommended. Insulin therapy started." In addition, patient's medical chart usually contains personal identifying information (PII) such as patient names, age, sex and date. Similarly, this has to be classified as PII and anonymized.

Our technique is built around the idea of organizing clinical narrative texts as facets of information, enabling the expression of clinical texts grounded in the way physicians think. It organizes these narrative texts loosely enough to support information seeking while providing intuitive structure for users to navigate the narrative text collections seamlessly.

4.5 Technical System Design

4.5.1 Convolutional neural Network (CNN)

In this thesis, we adopted a deep neural network with residual connections (skip connections) to classify clinical sentences into various semantic classes. Fig 4.7 shows a neural network diagram of our proposed model. The objective of the proposed model is to take a clinical document, process it and classify the various sentences into five semantic classes. Our proposed network architecture has 2 convolutional layers, 1 max-pooling layer, 2 fully connected layers (labelled as FC) and activation layers after each convolutional and fully connected layer, and a sigmoid layer at the end of the network.

This architecture uses residual layers that preserve the information from early layers and make it directly available to the later layers, skipping the intermediate layers. This is done by simply adding the output of the earlier layer to the output of the layer immediately before the later layer, i.e. what the input to the later layer would have been if there were no skip connections. This allows the output of the entire network to be informed in detail at multiple levels of compression simultaneously, meaning that the final output is informed by the information about the overall word or sentence structure from the early layers, as well as by the semantically compressed information in the later layers. In this neural network, skip connections also allow for efficient training of the early layers, since the error is directly propagated from the later layers back to the earlier ones; minimizing the vanishing gradient.

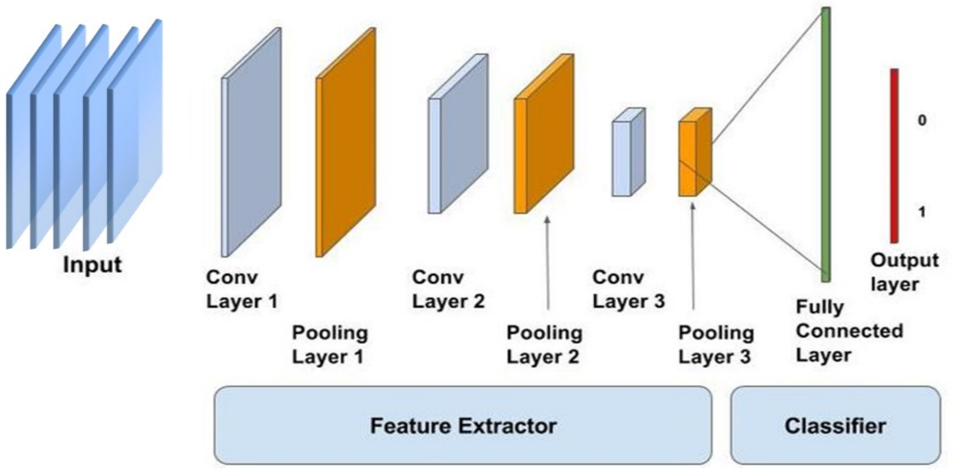

Figure 4.7 input/output configuration

The table below provides the input / output information of all the layers in our CNN model

Table 4.2: Input/output configuration

LAYER	NAME	VALUES
1	**Input Layer (I)**	
	Size:	2000
	Dimensions:	(40, 50, 1)
	Padding:	required
2	**Hidden Layer(s) (H)**	
	Convolutional layer	
	Dropout:	None
	Activation Function:	tanh
3	**Convolutional layer**	
	Dropout:	None
	Activation Function:	tanh
4	**Pooling Layer: 1D**	1D
5	**Fully connected Layer**	
	Dropout:	None
	Activation Function:	tanh
6	**Fully connected Layer**	
	Dropout:	None
	Activation Function:	tanh
7	**Output Layer (O)**	
	Size:	5 (Sentence Types)
	Activation Function:	Sigmoid

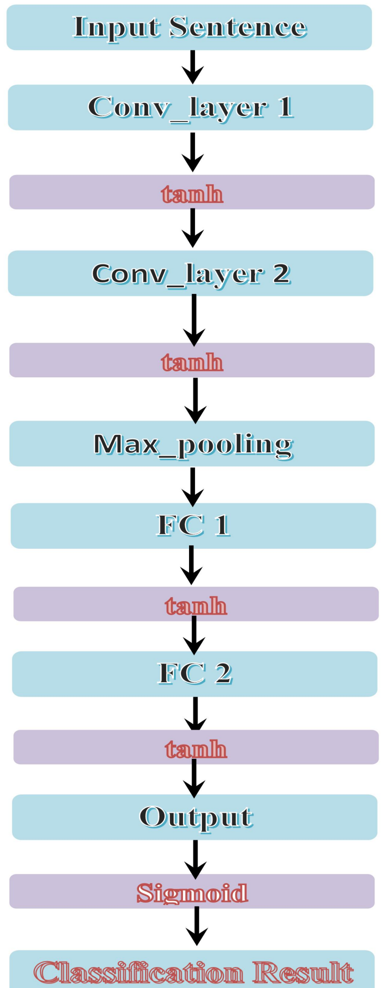

Figure 4.8: Convolutional neural network

To convert the plain convolutional neural network to the residual version, we added the shortcut connections, as shown in the figure 4.2 below. The solid line shortcuts are identity mapping. When the dimensions increases there are 2 options (dotted line shortcut):

i. The shortcut still performs identity mapping with extra zero entries padded to increase the dimensions. This option introduces no additional parameter.

ii. The projection shortcut in F(x{W}+x) is used to match dimensions (done by 1×1 convolutions).

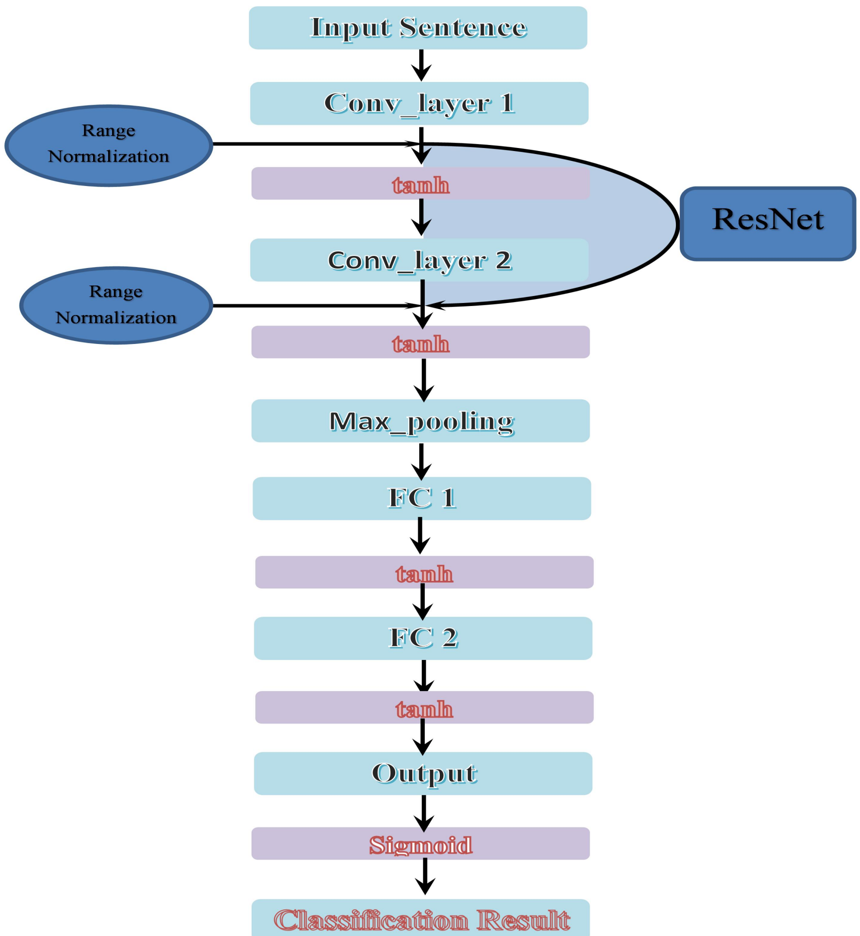

Figure 4.9: Convolutional neural network with residual connections

We used sentence classification model based on Convolutional Neural Networks (CNN), to automatically extract high-level semantic information of clinical documents and an automatic sentence classification model that can map sentences of a given clinical document into set of pre-defined categories. Deep convolutional neural networks employ multiple layers to learn hierarchical representations of data producing state-of-the-art results. However, deep neural network training is challenging (Glorot and Bengio, 2010). The work of Sutskever et al. (2013) has presented a detailed study on the challenges of training deep neural networks. In the recent past, the availability of high performance computing systems like GPUs and efficient training schemes like dropout (Srivastava et al., 2019), normalization techniques such as batch normalization (Ioffe and Szegedy, 2015) have made it possible to train deep neural networks. These models have also extended to natural language processing (NLP). In this thesis, we used a deep convolutional neural network to build predictive models for clinical textual representations of medical concepts. In particular, we used ResNet, a deep residual network proposed by (He et al, 206). Deep neural networks have been shown to be more effective at classification tasks. However, increasing the depth of a neural network often makes it more difficult to train due to the vanishing gradient problem (He et al, 2016). In this thesis, we designed residual network architecture (ResNet) to overcome some of the problems encountered in deep neural networks. More specifically, we employed the use of residual compounds to overcome the vanishing gradient problem (He et al, 2016). We used convolutional neural network to encode sentences by mapping an input sentence into a continuous vector representation. Therefore, the input data (each clinical text) of our CNN will be small; in particular it will be represented by a $n \times m$ matrix $where\ n$ is the number of words in the input sentence and m is the dimension of word-embedding space; n can be at most in range from 20 to 40 and usually in range from 2 to 5.

Due to small size of input (usually consisting of 2-5 words), the number of the convolutional layers can't be large. In general, deep convolutional layers can achieve better performance, which is desired for large size of input data, but not small data; otherwise, the deep convolutional layers will destroy any patterns of the small input data. So, in our design, we used 2 convolutional layers (Conv_layer 1 and Conv_layer 2) and a maximum pooling layer (Max_pooling) can be used for our small input data. And the feature numbers of each convolutional layer can be equal to 8 (or 4). The horizontal size of the convolutional window is the same as m because each row of input matrix is a word.

After each convolutional layer, the range normalization (RN) has to be followed before activation, function of which will be set to tanh function. The residual network (ResNet) which is the type of building (or bottleneck) block is added between two convolutional layers.

The 2 full connected layers (FC 1 and FC 2) are followed after 2 convolutional layers and pooling layer, the last one (FC 2) of which gives us the output for classification: 5×1 matrix with the 5 probabilities to be classified into *symptoms*, *diagnosis*, disease, *treatments and PII*, respectively.

The graphs of the activation functions tanh(x) and sigmoid(x) are shown in Fig. 4.9

Figure 4.10: The graphs of the activation functions tanh(x) and sigmoid(x)

tanh(x) is defined in $(-\infty, +\infty)$ and returns the values in [-1, 1]; the value of this function will be rapidly saturated with the increase in the absolute value of x. sigmoid(x) is also defined in $(-\infty, +\infty)$, but returns the values in [0, 1]; for the comparison with tanh(x), the value of sigmoid(x) will be relatively slowly saturated with the increase in the absolute value of x. The output values have the meaning of the probability to be classified into various categories, so its values should lie in [0, 1].

4.5.2 Using range normalization (RN) technique to address covariate shift and vanishing gradient problems

As mentioned in the literature, training deep neural networks is a challenging problem due to the distributed nature of each layer's inputs, which are always changing during training as the parameters of the previous layers change. It therefore slows down training because it requires lower learning rates and careful parameter initialization. This problem is called internal covariate shifting and is addressed by normalizing layer inputs (Ioffe & Szegedy, 2015). With this challenge in mind, we proposed the use of range normalization to address the above problems. Range normalization was implemented to accelerate the training of our deep neural network i.e. to reduce the total training time and improve the accuracy of the trained models.
After each convolutional layer the range normalization is applied. The range normalization function is used to map the data in a desired range (ex. [0, 1] for this case) through a simple linear transformation. Assume there are n numbers x_i (i=1, 2, …, n) which have to be mapped in a range [0, 1]. Then the result y_i (i=1, 2, …, n) can be obtain using the following equation:

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}},$$

where $x_{\min}$ is the minimum value of x_i and $x_{\max}$ is the maximum value. Because this is, of course, the linear function, the minimum value of y_i is obtained when x_i is equal to $x_{\min}$ and so is the maximum value of y_i. If we substitute the $x_{\min}$ into x_i, we obtain $y_{\min} = 0$. Similarly, $y_{\max} = 1$ can also be obtained. The new numbers y_i will therefore be distributed in the range [0, 1] as desired. Note that there may exist the special case, $x_{\min} = x_{\max}$, which means all the values of x_i are the same ($x_i \equiv x_{\max}$). In this case, the denominator of the above equation is equal to 0, which yields "the division by zero." In such a case, we can set y_i's to 0.5. Range normalization is simple to implement and does not increase the complexity of the CNN.

There is another reason for applying range normalization. And due to the reason mentioned above, the input matrix is too sparse; it has a lot of elements with vanishing values. The output of each convolutional layer will be very small and extremely vanishes after activation layers (tanh), due to which the relevant final classification results can't be obtained and the convergence of our CNN model will be guaranteed. In order to avoid this problem, the normalization of the output of each convolutional layer is needed.

There are two types of normalizations; batch normalization and range normalization. The former has been successful in image processing field such as classification, face recognition and verification, but has been shown to exhibit poor performance for the NLP, especially text classification which may result in the sparse input matrix. The latter can help us with the extension of outputs from vanishing region to the relevant region [0, 1] via simple linear transformation; this can solve vanishing problem!

4.5.3 Training and testing Datasets

To evaluate a model, data is often divided into two sets, training and test data sets, to be used in the evaluation of classification models. The model is then built (its parameters are determined) using the training set, and its performance is evaluated using the test set (keeping the parameters constant). In this thesis, the dataset was split into training dataset and a testing dataset. Training data set was used to train the classifier so that it will be able to learn and predict the required classes of the various sentences in a patient medical chart. The testing data was used to classify the unseen data. The split used was 70% for the training and 30% for the test data. We train our classifier with training data. During testing, we introduce new samples (test data) to test the proposed model.

Table 4.3 Descriptive statistics of dataset (Clinical medical charts)

Partitioning of patient data	
Total Records	61,300
Training Records	42,910
Testing Records	18,390

The suggested classifier learns to categorize a given phrase input into the corresponding output (semantic class) using training data in the training process (a). A feature vector is created from the text provided by the feature extractor. The machine learning method creates a model from pairs of feature vectors and semantic classes (such as Subjective, Objective, Assessment, Plan, and personal identifying information). Unseen text inputs are converted into feature vectors in the prediction phase (b) by the feature extractor. The model is then given these feature vectors, producing projected tags (again Subjective, Objective, Assessment, Plan and personal identifying information).

i. **Feature Extraction:** Feature extraction is used to extract vectors containing information describing the properties of the input data. The proposed model uses two layers of convolution to extract relevant features from clinical sets of any size. The word embeddings generated by unsupervised pre-training was used (Mikolov et al., 2013).

ii. **Labels:** Labels are the predefined classes that the proposed model will classify or predict. We trained a classifier on a labeled dataset (a set of examples that have been labeled). After training the classifier on labeled training data, we test on the unseen data.

iii. **ML Algorithm:** It is the algorithm which is used to classify data. In our case, we used a convolutional neural network with residual connections. The text classification approach chosen in this work is a model that is a combination of neural networks for classification and residual/skip connections. Fig. 4.1 shows a block diagram of the neural network.

iv. **Classification Model:** A model which has been trained on the historical dataset and it can be used to can perform classifications (i.e. predicting different classes based on the input).

4.5.4 Classification process flow

Sentences recognition in clinical documents can be simply considered as a classification problem of text according to pre-labelled classes. In this case, it requires collecting clinical documents, labelling them, pre-processing the documents in order to extract most information possible, generating word vector models from medical charts data corpus and then ultimately training the classifiers to classify the various clinical sentences. Figure 4.11 shows the architecture of the model. Steps are as follows:

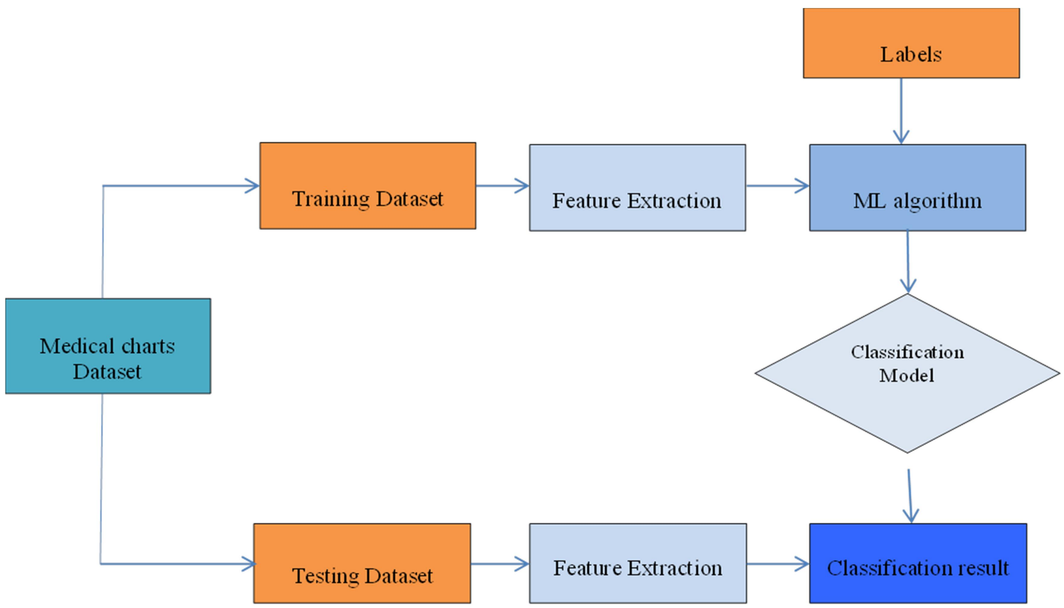

Figure 4.11: Training and testing process flows

An end-to-end clinical concept classification model is made up of the following components:

4.6 Implementation Overview

The goal of this phase was to transform clinical narrative documents into quantitative features for training. To do this an algorithm was designed and implemented. The algorithm takes clinical concepts as input and classifies them, outputting a class for each concept indicating which class it belongs to.

Algorithm

Input: Sentence S with n words.
Output: P(y): Probability of each label.
Encode S into vector $x \in \mathbb{R}^{vw}$ $using$ CNN.
Initialize base layer: $z0 = w_0 x + b_0$
for i = 1, 2,….,n do
$q_i = \sigma(z_{i-1})G_i + c_i$

$$z_i = w_0 x + b_i + \sum_{t=1}^{i} W_t \, \sigma(q_t)$$

End

$$P(y) \ = \sigma(z_n)$$

We use the convolutional neural network to extract the semantic feature vectors of sentences (medical concepts) and map them to a feature space, finally we use the classifier to calculate the probable probability of each medical concept and select the one with the highest probability.

The main algorithm can be divided into four modules which can be run independently:

4.6.1 Clinical narrative texts corpus

The functionality of our artefact is demonstrated using a corpus of clinical notes "medical transcriptions" retrieved from MTSamples website (http://www.mtsamples.com). This is a collection of publicly available corpus of transcribed clinical notes. We created a detailed annotation guideline to annotate transcribed medical notes: (1) Subjective, (2) Objective, (3) Assessment, and (4) Plan. In addition we added synthetic personal identifying information (PII) section to make them complete as the original PII had been removed to preserve privacy. The clinical text corpus was made of 61,305 sentences/phrases extracted from clinical notes. The class label was made up of five classes: Subjective, Objective, Assessment, Plan, and PII). The distribution of sentences/phrases across clinical information categories is as follows: Subjective = 20,307, Objective = 18,371, Assessment = 8,282, Plan = 8,735 and PII = 7,567.

The mmeasures of our data is described using the following label density and label cardinality as shown by the equations below:

The label density denoted LD, $\mathrm{LD} = \frac{1}{|S|} \sum_{i=1}^{|S|} \frac{C_i}{C}$ (1) where C_i is is the label set for S_i

The label cardinality denoted by $\mathrm{LC} = \frac{1}{|S|} \sum_{i=1}^{|S|} C_i$ (2)

Using the above, the LC and LD for our dataset are computed to be 1.03 and 0.41 respectively.

4.6.2 Pre-processing

According to (Uysal & Gunal, 2014), the objective of pre-processing is to remove irrelevant pieces of text which may obscure meaningful patterns and lead to poor classification performance and redundancy in the analysis.

Initially, we pre-process the patient medical text chart to identify sentence boundaries, and structure the text so that each sentence occurs on a separate line. This is necessary because our basic unit of semantic interpretation is a sentence where our objective is to classify and assign semantic classes to individual sentences and not the entire document. After identifying the sentences, the next step is tokenization (the separation of punctuation from words). To create word vectors of the input sentences, the input sentence are separated into words; the sentence may be composed of various types of punctuation marks such as ",", ".", ":", "/", "(", ")", "-", "-", … and these marks should be removed; in our code, they are replaced by space " "; then the input sentence will be separated into words by space. For each word in the input sentence, checking if it is in the word2vec dataset or not should be performed; if yes, the corresponding word2vec vector will be inputted in the input matrix, but if not, the empty row with zeros will be added. If the number of words is larger than 40, the last words (besides first 40 words) will be ignored.

4.6.3 Distributional representation of sentences

Before training our deep neural network and using it classify clinical documents, we needed to convert the raw text document into a numerical representation that will be our input to our classifier. To achieve this, we must first convert individual words in a sentence into a vector embed, and then concatenate those embeds into a sentence embed and form a matrix of the size of the number of words in the document times the dimension of the word embeddings.

4.6.3.1 Word embedding

The next step after design of a deep learning model is word-embedding which transforms the words into multi-dimensional vectors. The word is the atomic representation of a document which is the same as pixels in image processing. Word embeddings which is also called distributional vectors follow the distributional hypothesis, where words with similar meanings tend to occur in similar context. Thus, these vectors always capture the characteristics of the neighbouring words. It has the advantage of capturing similarity between words. The similarity is measured using similarity measures such as cosine similarity. In deep learning models, word embeddings are used as the first data processing layer in a deep learning model (Young et al, 2018). Word embedding can be defined as the mapping of words or phrases from the vocabulary into vectors of real numbers. A word vector is a position in a high-dimensional space which represents the respective words semantically. In that space, words that have similar meanings lie closer to each other. Hence, synonyms have almost the same vector and lie close to each other. In our deep learning model, we need vector representations for each of our sentences in a medical chart. Usually, machine Learning algorithms are incapable of processing plain *narrative text* in their raw form, and therefore requires text input to be mapped into numeric vector representations. The resulting vectors (array of numbers) contain numeric values which can be easily processed by a machine learning algorithm. There exist several methods of creating word vectors which have been applied by many researchers in the literature. The most basic word Embedding technique is known as Bag of Words (BoW) which usually maps each word from a given vocabulary $V = \{wi\}ii \in N$ as a one-hot encoded vector where it contains all zeros, except a 1 at the position corresponding to the index representing the word. One hot representation has traditionally been used to encode words into word vectors for deep learning neural models, where the position where the word exists is represented by 1 and 0 otherwise using the available dictionary of data. However, the challenge with this technique is that the size of the input vector, and which translates into the number of neurons in the input layer of a neural network, depends on the size of the vocabulary (ELAffendi and ALRajhi, 2018). Empirical research has shown that the training time for text classification neural models grows exponentially with the size of the vocabulary when one hot encoding is used (ELAffendi and ALRajhi, 2018). For example, if the size of the vocabulary is 10,000, then the size of the input vector will be model 10,000 implying 10,000 neurons in the input layer (ELAffendi and ALRajhi, 2018). Therefore, it always results in a sparse vector; with the dimensionality equal to the size of the dictionary and all the elements of this vector are zero except the position where the word exists. In addition, it is not memory efficient and it does not represent semantic relations between the words such as similarity of the words. One of the major limitations of hot representation methods is the fact it often ignores the contextual information or word order in texts and remains unsatisfactory for capturing the semantics of the words (Lai et al, 2015).

Due to the limitations of one hot encoding, word embeddings are currently used to create word vectors. One of the major advantages of word embedding models is the ability to learn the relationship between words by being trained on a large corpus. They are based on the distributional hypothesis (Harris, 1954) which states that similar words appear in similar contexts. Two very common algorithms are Word2Vec (Mikolov et al, 2013a, b) and GloVe (Pennington, Socher, & Manning, 2014). Both are used to encode words into an arbitrary dimensionality based on the contexts these words occur in. For Word2Vec, the context is a window of surrounding words. For GloVe, it is the whole sentence or document. On the other hand, word embeddings such as Word2Vec (Mikolov et al, 2013a, b) and GloVe (Pennington, Socher and Manning, 2014) have proven to be effective in representing the semantics at word level with a distributed representation.

A recent popular approach is, distributed word embedding which tries to address the limitations of one hot representation. In particular, the uses of neural models that exploit word embeddings have recently achieved state of art results on text classification tasks (Goldberg, 2015). The idea behind word embeddings is to use neural models in order to transform words to feature space so that similar words are represented by vectors with small distance between one another. They are often trained using neural language models and are becoming widely used in text classification with Convolutional Neural Networks (CNNs). Since the pioneering works of Collobert et al(2011), the use of convolutional neural networks and distributed word representations(word embedding) language models have become common for text classification problems (Kim, 2014; Conneau et al., 2017). Its advantages include the ability of capturing context of a word in a document, semantic and syntactic similarity, relation with other words, etc. Word2vec is popular method used to transform texts into a numerical vector space.

It is a pre-trained word-embedding model which has been trained on billion words from Google News; the dimensionality of this vector is 300; if the unknown word (which is not contained in the training dataset, Google News) will be initialized randomly.

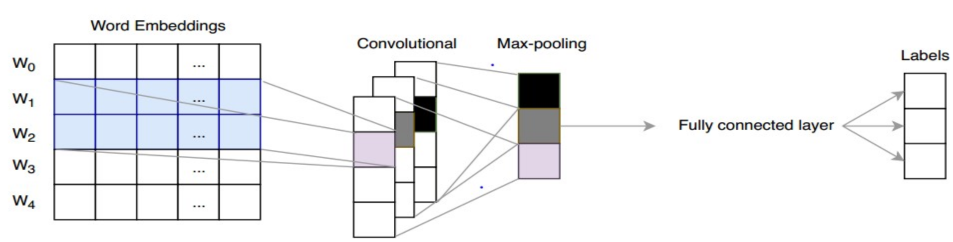

Figure 4.12: Block diagram for a simple Convolutional neural network

There exist many pre-trained word-embedding models; for example, word2vec vectors which have been trained on billion words from Google News; the dimensionality of this vectors is 300; if the unknown word (which is not contained in the training dataset, Google News) will be initialized randomly.

For this case, pre-trained GloVe (Global Vectors for Word Representation) word vectors have been used in this project for word-embedding in conjunction with supervised machine learning methods based on deep learning using convolutional neural networks and recurrent neural networks. It is similar to Word2vec and it can embed words as mathematical vectors. However, the difference is the method used to capture similarity between words which uses count-based technique. The main idea behind Glove embedding is to construct a huge co-occurrence matrix between the words found in the training corpus of shape V × C with V being the vocabulary of the corpus and C being the context examples (Dynomant et al., 2018). GloVe is an unsupervised learning algorithm, the purpose of which is obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

The glove.6B.zip has been chosen; it contains several dimensional word2vec vectors (for example: 50D, 100D, 200D, 300D) and the 50D vector library has been selected for this classification of patient medical chart; i.e. each word is converted into 50D vectors with the positive and negative values; for example, “and” is converted into vector:

{0.26818, 0.14346, -0.27877, 0.016257, 0.11384, 0.69923, -0.51332, -0.47368, -0.33075, -0.13834, 0.2702, 0.30938, -0.45012, -0.4127, -0.09932, 0.038085, 0.029749, 0.10076, -0.25058, -0.51818, 0.34558, 0.44922, 0.48791, -0.080866, -0.10121, -1.3777, -0.10866, -0.23201, 0.012839, -0.46508, 3.8463, 0.31362, 0.13643, -0.52244, 0.3302, 0.33707, -0.35601, 0.32431, 0.12041, 0.3512, -0.069043, 0.36885, 0.25168, -0.24517, 0.25381, 0.1367, -0.31178, -0.6321, -0.25028, -0.38097}.

In this library, there are 400 000 words such as daily words, numbers, punctuations, etc. In using pre-trained word2vec library, there is an important challenge: if the unknown word is encountered, how will it be treated? The usual method to treat unknown word (i.e. not exists in the library) is randomly initializing them, which maybe mislead our CNN classifier model to incorrect result. For treating unknown word, let us consider how human (e.g. a doctor) treat unknown word in reading text (the patient medical charts). When reading a book and encountering unknown word, human can skip the word and basically understand the meaning of the given text without randomly guessing unknown word. Frankly speaking, classifying is easier than reading. For example: suppose “*Patient advised to take bed rest and plenty of fluids. Ibuprofen prescribed*” is given and *Ibuprofen* is “unknown” word. The current task is classifying which category these sentences belong. Human can classify these sentences into *Treatment* based on the former sentence even if they don’t know the word *Ibuprofen*, which means a few unknown words could not have a central role or could be ignored in classifying. So, the “unknown” words have been treated as blanks, but not randomly; i.e. the unknown word will be converted into zeros (skipping), but not random values (guessing).

4.6.3.2 Sentence embeddings

In most NLP tasks, a sentence is a fundamental unit of processing. People describe health concerns and symptoms using many different sentences e.g. "I have bad diarrhoea and tummy pain. One of the fundamental tasks in NLP is identifying sentences, or what is more formally referred to as sentence boundary detection (Griffs et al., 2018). Therefore, processing of a clinical document consists of identifying medical concepts which are sentences. We would like to obtain sentence embeddings which has more semantic information than word embeddings. Therefore, we have used sentences as our unit of analysis since our assumption is that the sentence is used to describe a medical concept. In the context of our algorithm, a sentence is defined as a sequence of tokens that provides semantic information e.g. symptom. A sentence contains tokens which are defined as words, numbers, or symbols. We refer to a sequence of consecutive tokens as a sentence.

As mentioned before, clinical documents can be described by a number of clinical concepts such as Subjective, Objective, Assessment, Plan and personal identifying information such as names. These clinical concepts terms are often expressed in multi-word phrases. We therefore need Machine learning (ML) models which can be trained to automatically map documents to these clinical concepts, allowing classifying very large text collections, more than could be processed by a human being. These concepts are basically sentences, and therefore an important task of understanding these sentences is mastering the composition of sentence meaning and knowing the context of the sentence is important information for grasping the word sense (Shin et al., 2018). In practical situations, a natural language is used to facilitate the exchange of ideas among people about something. These ideas converge to form the "meaning" of an utterance or text in the form of a series of sentences. The meaning of a text is called its *semantics.*

Before training the neural network and using it for sentence classification tasks, we first generate a numerical representation of the various sentences that will serve as an input to the neural classifier. This work proposed a novel approach of generating efficient sentence embeddings based on word embeddings which could outperform state-of-the-art sentence embedding algorithms on several tasks. Just like word vectors, the same concept can be applied to sentences where vectors with similar sentences lie close to each other in a high-dimensional space. A sentence embedding is a vector representation, where sentences are mapped to sequences of numbers (vectors) that represent their meaning. An embedding is a fixed-length vector typically used to encode and represent a word or a sentence. In this thesis, we use Convolutional neural networks to extract fix length features from word sequences, which is a patient medical chart in our case. In our approach, we use a pre-trained word embedding model which maps each word to a vector representation. The vectors for multiple word embeddings belonging to the same sentence are then combined to form a single sentence embedding. The patient chart is usually made up of two or more sentences expressing some medical concepts which can be Subjective, Objective, Assessment, Plan and personal identifying information. Therefore, we treat each medical expression as a single sentence, separating them using sentence tokens located at the end of each sentence. Similarly, a sentence is made up of two or more words. Therefore, a sentence S with n words w1, w2, , wn-1, wn is mapped into a set of n-dimensional real-valued vectors x1, x2, ….xn-1, xn using word embedding. Each word is mapped into a single word-vector xi where i range from 1, 2 ……….n. To obtain the vector representation of sentence S, we concatenate the word vectors w1, w2, ….. ,wn-1, wn to obtain a sentence vector X. This is summarized in figure 4.13 as shown below.

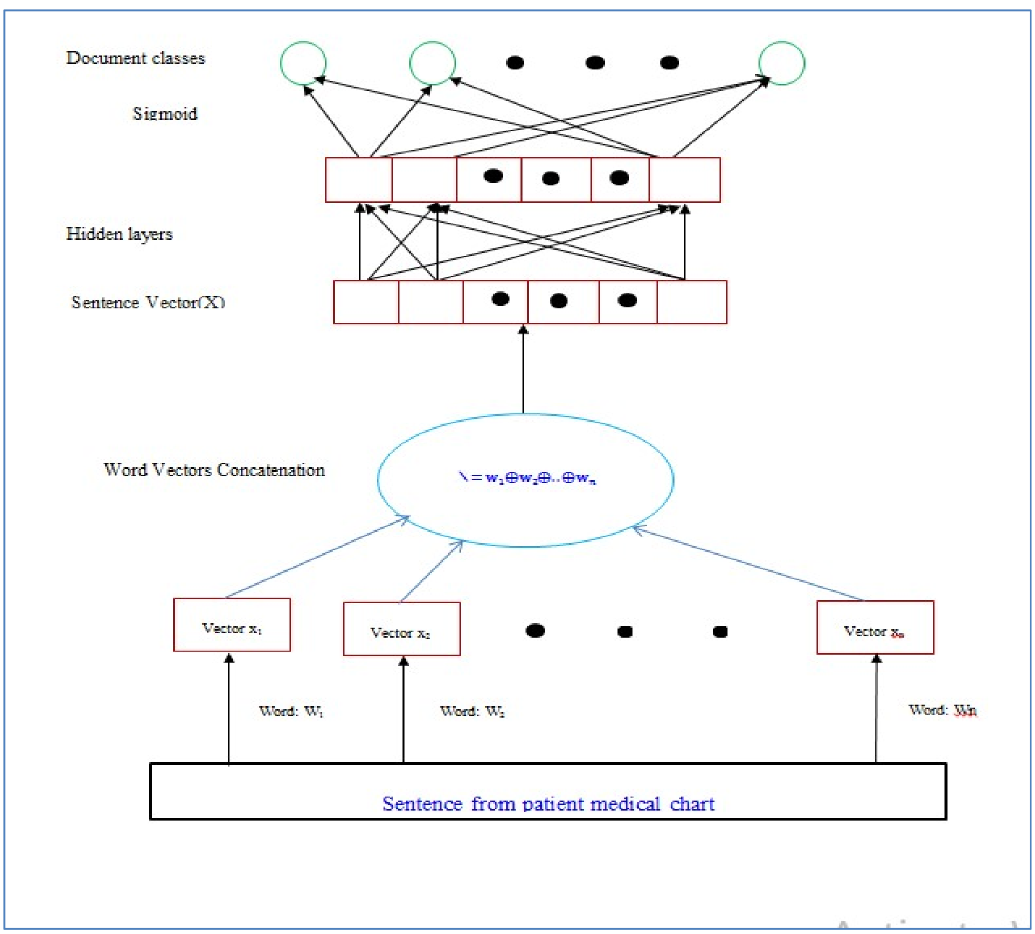

Figure 4.13: Creating medical sentences vectors.

In our proposed approach, a clinical document is transformed into a matrix which is the input to neural network, with each row representing a sentence. The neural network convolutional layer "scans" the matrix, breaks it down into features, and judges whether each feature matches the relevant class or not.

Table 4.4: Architectural Hyper Parameters and Training Details

Type of the layer	Position of Residual Connections	Shape of the output feature	Number of parameters
Convolutional layer (C1)	C1-C2	(38,1,5)	3×50×5+5=755
Convolutional layer (C2)	-	(38,1,5)	3×1×5+5=20
Max pooling (M1)	-	(19, 1, 5)	0
Full connected layer (FC1)	-	(256)	19×5×256+256=24576
Full connected layer (FC2)	-	(64)	256×64+64=16448
Output layer		(5)	64×5+5=325

4.6.4 Classification

To distinguish different semantic classes of clinical sentences in a given clinical document, a classifier was developed to classify clinical sentences in a medical chart into different semantic classes. In this thesis the clinical document were split into sentences and all sentences got tagged with a semantic class (topic). The classification takes the whole dataset of sentence embeddings and classifies them in order to form distinct categories of clinical sentences. The clinical concept classes are returned as the output of the algorithm. In the following section the algorithm and its implementation will be presented in further detail.

Our main task in this thesis is to classify clinical concepts which are basically sentences made of one or more words in order to identify key concepts in a patient medical chart, such as symptoms, diagnosis etc. The proposed model receives the clinical text and the corresponding categories; for example, "*unexplained weight loss*" and *symptoms*. The former can be represented via word-embedding procedure as shown below and the latter can be represented by one-hot representation (1, 0, 0, 0, 0), where 1 means the inputted sentence is classified into *symptoms* and the remaining zeros denotes it is classified into neither *diagnosis, disease/conclusion, treatment, personal identifying information (PII)*. The former will be fed into the proposed, while the latter (each element denoted as y_1^*, y_2^*, y_3^*, y_4^*, y_5^*) will be used for evaluation of loss function and training of the proposed.

The input sentence e.g. "*unexplained weight loss*" has 3 words *unexplained*, *weight* and *loss* each will be transformed into n-dimensional (50-dimensional) word2vec vector using word-embedding.

Let $\mathbf{w}_1$, $\mathbf{w}_2$, $\mathbf{w}_3$ represent the individual words in the sentence. Therefore "*unexplained weight loss*" is converted into 3×50 matrix X as shown below.

$$X = \mathbf{w}_1 \oplus \mathbf{w}_2 \oplus \mathbf{w}_3$$

Where $\oplus$ denotes concatenation of word2vec vectors and the ith column of X is the embedding vector corresponding to word wi. Because of different lengths of input sentences, the resultant matrix X has different number of rows, which is not valid for CNN model; therefore, the size of input matrix has to be fixed into n rows and 50 columns i.e. we need to encode variable length sentences into fixed length vectors, in a way that preserves the sentence meanings i.e. representing the variable-length sentence as a fixed length vector with the semantics of natural language. The words in input sentence can't be omitted; that is, n must be the largest number of words in all the possible input sentences. For the shorter sentence, the blanks (corresponding to row vector with 50 zeros) can be added to obtained fixed matrix size of input. The input matrix will be too sparse since the input sentence usually has 2-5 words.

For the 1st convolutional layer (Conv_layer 1), the filter $\Lambda_1 \in \mathbb{R}^{3\times 50}$ with a window of 3 words is used, which produces feature maps (as shown in Fig. 4.5):

$$x_1 = X * \Lambda_1 + \epsilon_1$$

where $x_1 \in \mathbb{R}^{38\times 1}$ (i.e., row vector) with valid padding [due to valid padding, the number of rows will be 40 (original number) – 3 (size of filter window) + 1 = 38],

* is the convolution operator,

$\epsilon_1 \in \mathbb{R}^5$ is bias factor which appears due to sparseness of the matrix X.

The range normalization and activation follow after this convolutional layer and gives x_1^*.

We used 5 filters for the first convolutional layer.

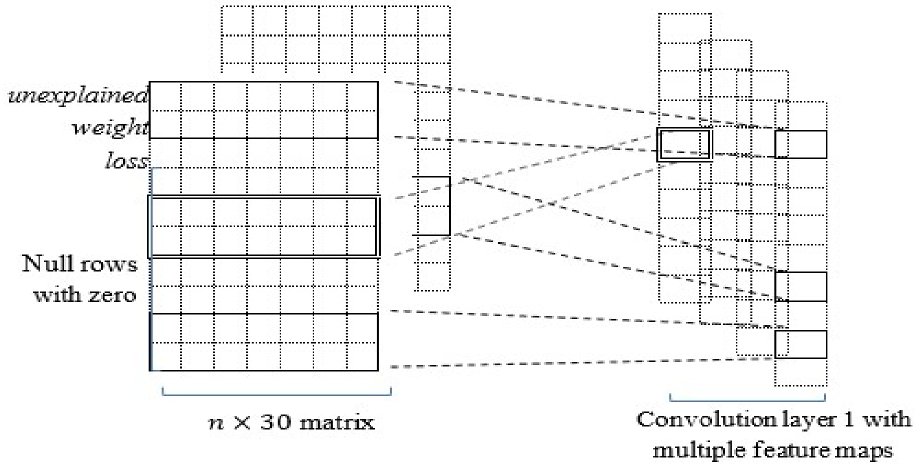

Figure 4.14: Convolution for input matrix.

For the 2nd convolutional layer (Conv_layer 2), the filter $\Lambda_2 \in \mathbb{R}^{3\times 1}$ with a window of 3 words is used, which gives produces feature maps (as shown in Fig. 4.6):

$$x_2 = x_1^* * \Lambda_2$$

where $x_2 \in \mathbb{R}^{38\times 1}$ with same padding (same padding gives us the same number of rows), * is the convolution operator, and $\epsilon_2 \in \mathbb{R}^5$ is bias factor. We also used 5 filters for the first convolutional layer. After the range normalization, the output x_1 of the 1st convolutional layer is added before activation layer (Resnet). After Max-pooling layer, all the multiple features are concatenated into one row vector before 2 FC layers.

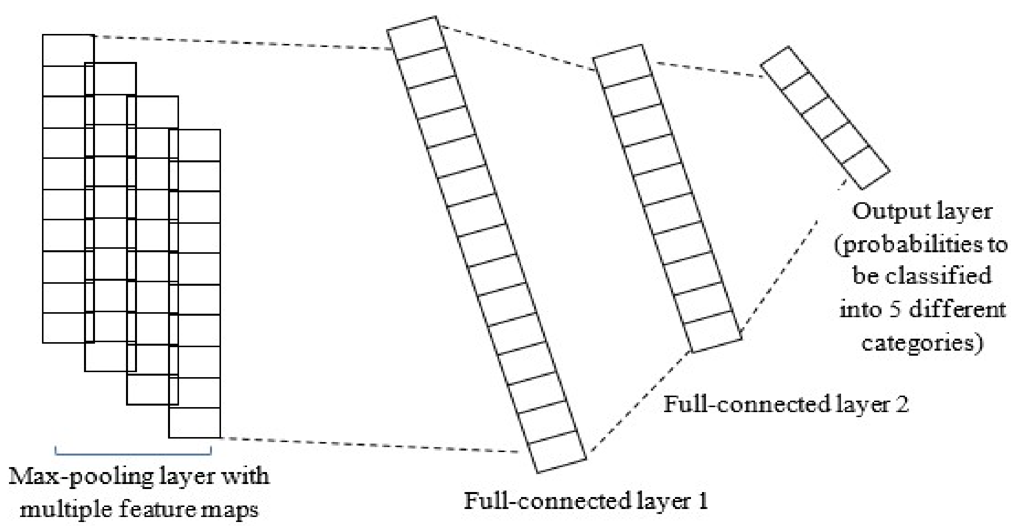

Figure 4.15: The output of our CNN model.

After 2 full-connected layers, the final activation layer with sigmoid function

$$\sigma(t) = \frac{\mathrm{e}^t}{1 + \mathrm{e}^t}$$

will give the probabilities $y_1,\ y_2,\ y_3,\ y_4,\ y_5$ to be classified into 5 types of medical concepts(categories).

4.6.5 Loss function and Adam optimizer

The loss function is very useful in deep learning because it focuses on minimizing classification error. It's used to determine how much the predicted value differs from the actual label. It is a non-negative value that emerges from the final classification layer, where the robustness and accuracy of the deep learning model improves as the loss function value decreases. We used the cross-entropy loss function as our loss function in this thesis. The performance of a classification model whose output has a probability value between 0 and 1 is measured by cross-entropy loss. The probability distribution between the true distribution y and the predicted distribution is measured by cross-entropy loss $\mathbf{y}^*$.

$$L(\mathbf{y}, \mathbf{y}^*) - \frac{1}{5}\sum_{i=1}^{5}[y_i^* \log y_i + (1 - y_i^*) \log(1 - y_i)],$$

Where $\mathbf{y} = (y_1, y_2, y_3, y_4, y_5)^{\mathrm{T}}$ are the classification probabilities?

And

$\mathbf{y}^* = (y_1^*, y_2^*, y_3^*, y_4^*, y_5^*)^{\mathrm{T}}$ is the given one-hot representation mentioned in previous subsection.

The Adam optimization (Kingma, and Ba, 2014) algorithm for deep learning which usually referred to as Adam optimizer was used for optimization of this loss function.

Table 4.5: Adam Optimizer

Optimizer	Value
Optimizer:	Adaptive Moment Estimation (Adam)
Loss Function:	Categorical Cross Entropy for the loss function (used for the optimizer)
Optimizing on:	Accuracy

The algorithm for training CNN model is given as follows:

i. Input the clinical text and the corresponding categories (which has been converted into relevant numerical values via word-embedding and preprocessing).

ii. Obtain the classification probabilities for 5 categories via CNN model.
iii. Calculate the cross-entropy loss function.
iv. Update the model parameters using Adam optimizer.
v. Iterate steps 1-4 until loss function vanishes.

Initially, at the beginning, the loss function may be large due to randomly initialized model parameters, but with the iterations of steps 1-4 and with the improvement of model parameters, the loss function will decrease from the original loss function value; until it vanishes. This is referred to as the convergence of model. The better the model, the faster the speed of convergence. In other words, the model takes less number of iterations (called epochs) for the model to converge. Therefore, the epochs (the number of iterations) it takes the model to converge will be used to evaluate the model's performance. As the loss function decreases, the classification accuracy increases by epochs.

For checking robustness of our CNN model, the test dataset (not belonging to training dataset) is fed into the model. For each clinical text, the model gives accuracy vector $\mathbf{y} = (y_1, y_2, y_3, y_4, y_5)^{\mathrm{T}}$ where all the values of the elements y_1, y_2, y_3, y_4, y_5 usually have the values in the range (0, 1) and denotes the probabilities for the inputted text to be classified into each category, respectively. Among them, the maximum value will be selected and the inputted text will be classified into the category corresponding to the maximum value. For the trained texts, "*unexplained weight loss*", the proposed may give nearly one-hot representation vector, for example (0.9, 0.02, 0.04, 0.03, 0.01), which tells "*unexplained weight loss*" and is classified into *symptoms*; for testing text, "*loss of appetite*" (which belongs to *symptoms*), the proposed may give (0.6, 0.2, 0.1, 0.01, 0.09) after normalization of the unit probabilities of each category and since the maximum value is 0.6, the inputted text "*loss of appetite*" is classified into *symptoms*. The classification accuracy will also be used for the evaluation of the proposed 's classification performance below.

4.7 Chapter summary

In this chapter, we described the detail implementation of the proposed artefact. We proposed a method for identifying and visualizing various information facets in a clinical narrative text document. Our approach is based on ML classifier that is used to predict the facets as accurately as possible, map labeled documents onto relevant groups and in a third step visually present information in a cluster map. We presented two techniques; deep learning model design and the visualization component.

CHAPTER FIVE: RESULTS AND FINDINGS

Two evaluation procedures were carried out in this study. First, we evaluated the classification algorithms derived from the visualization model to determine their effectiveness in classifying clinical narrative texts into different classes (Subjective, Objective, Assessment, Plan and PII). We also evaluated the range normalization performance of the proposed model against batch normalization. These are in line with research question RQ4. Secondly, the artefact was evaluated with the users as per Peffer's *et al.* (2006) Design Science Research framework. This is in line with research questions RQ5**.** We started by describing the experimental setup of our research, followed by detail experiments and performance results of different algorithms. We also present the results of user study evaluation. This is followed by a discussion of the results. For system evaluation, we outlined a listing and a brief description of all the experiments carried out and the different algorithms used; then followed by a tabular comparison of the results attained using different algorithms. The objective of comparing the algorithms was to establish whether the difference in performance attained using different algorithms was significant.

5.1 Experimental Results

To assess the effectiveness of our approach, we implemented a classification system for clinical sentence-level using range normalization as a regularization technique. We conducted a series of experimental studies to compare our proposed classification model against the baseline models. This section reports experiments carried out over the corpus as explained above. First, we divided the dataset into two parts, the first part, which contains 35,000 medical charts, for training, and the second part, which contains 15,000 medical charts, for testing.

As mentioned earlier, the evaluation of the proposed model's performance was made using two metrics:

i. The cross-entropy loss (Speed of convergence of training model),
ii. The accuracy of text classification for text input;

The classifier performance was evaluated using the above performance metrics.

A common cost function used to evaluate the performance of a neural network is cross-entropy loss. We measured the cross-entropy loss against the number of epochs. This is usually useful as it gives the number of epochs required to reach relevant classification accuracy for training data. We also measured the classification accuracy in classifying the untrained clinical document into relevant categories. We compared the cross-entropy loss, and classification accuracy of our deep convolutional neural network classifier with residual connections and range Normalization to a non-ResNet model and a ResNet model without Range Normalization, as described below.

5.1.1 Comparison of the proposed model against base models

5.1.1.1 Cross entropy loss

To see if adding range normalization to the model improves training speed, we ran a series of tests, including a comparison of other convolutional neural network models with and without range normalization. In order to argue in favour of the proposed model, we focused our experiments on our baseline models, whose performance was to be improved by our proposed layer normalization technique (range normalization technique). We iterated 20 epochs (the convergent speeds of our CNN classifier models are very rapid, so we set 20 epochs) for training our CNN classifier models; during this, we recorded the cross-entropy losses for each epoch. The results for the cross entropy loss are shown in Table 5.1 and Figure 5.1.

Table 5.1. The cross-entropy loss with epoch for the various types of CNN classifiers.

	Cross Entropy			
Epoch	CNN with ResNet and Range Normalization	CNN	CNN with Range Normalization	CNN with ResNet
0	0.40456180	0.39803580	0.25921010	0.13512650
1	0.05301021	0.09534214	0.10273490	0.00784123
2	0.01116922	0.00939236	0.09795706	0.00308964
3	0.00695690	0.00854493	0.09668896	0.00161631
4	0.00225344	0.00171603	0.09622138	0.00105125
5	0.00115580	0.02043436	0.09598779	0.00074064
6	0.00320921	0.00449354	0.09587640	0.00055878
7	0.00053290	0.00336803	0.09586036	0.00073536
8	0.00036959	0.00063999	0.09598557	0.00029756
9	0.00024338	0.00030177	0.09575519	0.00020379
10	0.00208383	0.04178076	0.09572953	0.00013329
11	0.00014354	0.05642569	0.09574534	0.00008750
12	0.00010803	0.01947598	0.09573305	0.00005652
13	0.00129322	0.00845496	0.03750850	0.00003669
14	0.00008831	0.00399874	0.00251975	0.00002352
15	0.00006125	0.00054936	0.00080457	0.00001524
16	0.00003831	0.00018242	0.00031239	0.00001007
17	0.00002246	0.00007754	0.00012878	0.00000646
18	0.00001190	0.00003520	0.00005320	0.00000428
19	0.00000617	0.01002902	0.00002272	0.00000281

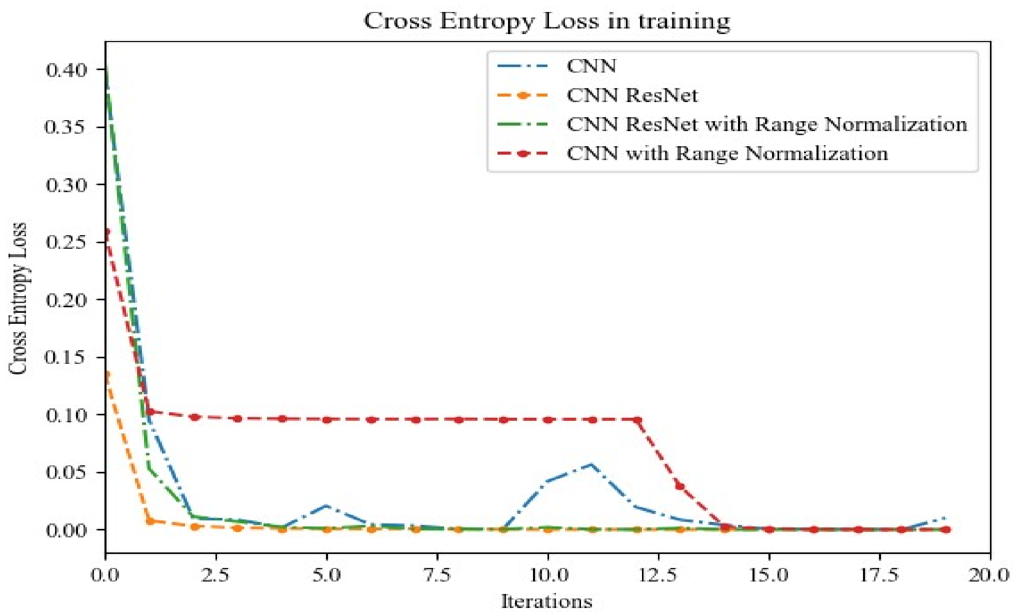

Figure 5.1: The cross-entropy loss vs iterations for the various types of CNN classifiers.

The convergence of convolutional neural network model is not stable; there are some spike increments in entropy loss at epochs 5, 11 and 19; this results in the sparse input matrix without the help of layer normalization technique. The convergent speed of convolutional neural network with range normalization is the slowest than the other models, which implies the residual/skip connections will play a central role in this case. The convergent speed of convolutional neural network with residual/skip connections and range normalization model is the most stable and fastest because of the combination of both range normalization and residual connections (skip connections). The goal of the experiments was primarily to determine which deep learning implementation work best for clinical text classifications. The experimental results show that the proposed model outperforms other deep learning classifications models in clinical documents classification task.

Range normalization (RN) is a technique to normalize activations in intermediate layers of deep neural networks. After each convolutional layer the range normalization is applied and this maps the data to a desired range (ex. [0, 1] in our case) through a simple linear transformation. From the above results, it can be argued that, a convolutional neural network with residual connections and range normalization improves the speed of training and therefore a good implementation in deep learning. From the experiments, we can conclude that a convolutional neural network with residual connections and range normalization primarily enables training with higher learning rates, which is the cause for faster convergence and better generalization. For networks without range normalization, we can see the slow convergence and activations growing uncontrollably with increased network depth, which limits possible higher learning rates. Therefore, it has been shown empirically that convolutional neural network with residual connections and range normalization is an effective classification model for clinical text classification tasks.

5.1.1.2 Classification accuracy

For the model accuracy, we iterated 20 epochs (the convergent speeds of our CNN classifier models are very rapid, so we set 20 epochs) for testing our CNN classifier models; during this, we recorded the classification accuracy for each epoch. The results for the cross entropy are shown in Table 5.2 and Figure 5.2.

Table 5.2: Classification accuracy with epoch for the various types of CNN classifiers.

	Classification Accuracy			
Epoch	**CNN with ResNet and Range Normalization**	**CNN**	**CNN with Range Normalization**	**CNN with ResNet**
0	0.45897850	0.45452680	0.64858430	0.84997570
1	0.96247930	0.90981010	0.83335840	0.99946060
2	0.99968980	0.99664660	0.83415570	0.99938420
3	0.99789630	0.99615670	0.83343670	0.99946060
4	0.99991910	0.99945610	0.83230370	0.99946060
5	0.99992810	0.97898990	0.83337160	0.99946060
6	0.99827840	0.99740180	0.83338750	0.99946060
7	0.99992810	0.99818850	0.83342560	0.99952800
8	0.99992810	0.99969430	0.83243900	0.99989660
9	0.99992810	1.00000000	0.83336030	1.00000000
10	0.99902460	0.97220220	0.83326760	1.00000000
11	0.99992810	0.99933470	0.83328350	1.00000000
12	0.99992810	0.99940660	0.83295640	1.00000000
13	0.99941110	0.99982920	0.96697890	1.00000000
14	0.99992810	0.99885370	1.00000000	1.00000000
15	0.99995500	0.99997300	1.00000000	1.00000000
16	1.00000000	1.00000000	1.00000000	1.00000000
17	1.00000000	1.00000000	1.00000000	1.00000000
18	1.00000000	1.00000000	1.00000000	1.00000000
19	1.00000000	0.99615220	1.00000000	1.00000000

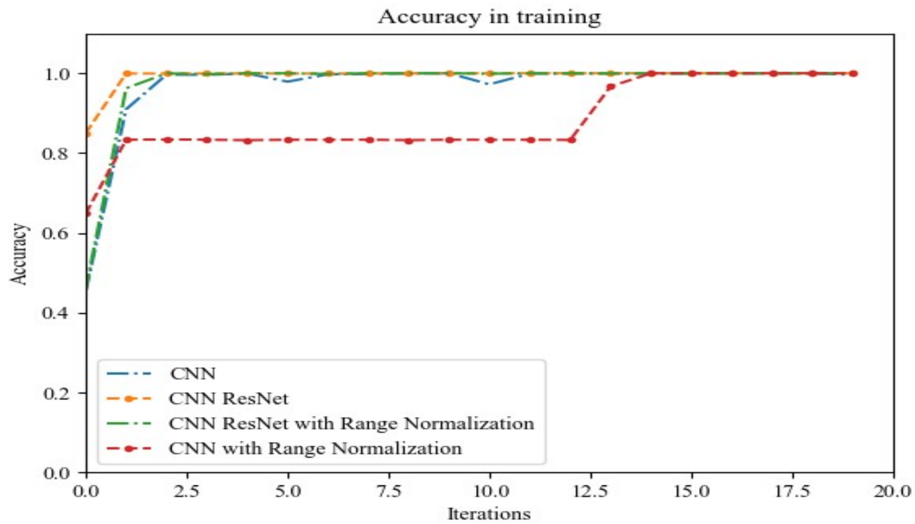

Figure 5.2: Classification vs. iterations for the various types of CNN classifiers.

As shown in the figure above, the classification accuracy of convolutional neural network model is not stable; there are some decreases of accuracy at epochs 5 and 11. The accuracy of convolutional neural network model with range normalization model is the lowest compared with the other models while the accuracy of convolutional neural network model with residual/skip connections with range normalization is the highest.

5.1.2 Range normalization versus batch normalization

5.1.2.1 Cross entropy loss

In this experiment, we compared the convergence behaviour of batch normalization against range normalization. We trained both deep convolutional neural network using batch normalization and range normalization using clinical narrative text datasets described above. We then measured the convergence speed (cross entropy loss) for each scenario.

Table 5.3: Results - Cross entropy loss

Epoch/Iteration	Cross entropy loss	
	CNN with ResNet and Batch Normalization	CNN with ResNet and Range Normalization
0	0.09610238	0.4045618
1	0.01463564	0.05301021
2	0.00584911	0.01116922
3	0.00230049	0.0069569
4	0.00044792	0.00225344
5	0.00014934	0.0011558
6	0.00005993	0.00320921
7	0.00002512	0.0005329
8	0.00001068	0.00036959
9	0.00000458	0.00024338
10	0.00000197	0.00208383
11	0.00000085	0.00014354
12	0.00000037	0.00010803
13	0.00000016	0.00129322
14	0.00000007	0.00008831
15	0.00000003	0.00006125
16	0.00000002	0.00003831
17	0.00000001	0.00002246
18	0.00000001	0.0000119
19	0.00000000	0.00000617

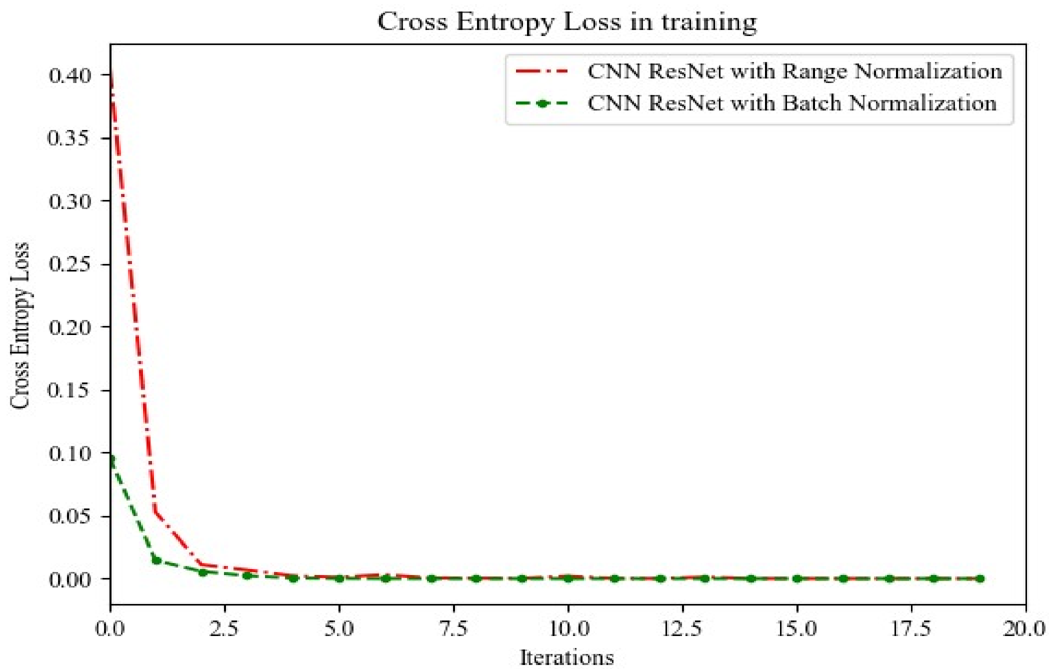

Figure 5.3: Cross-entropy loss for the CNN training as a function of the epoch number.

As shown in the above figure 5.3, range normalization shows high convergence speed compared to batch normalization. Batch normalization accelerates the speed of convergence for training at the starting epochs, while the final convergence speeds are the same for both batch normalization and range normalization. Therefore, it has been shown empirically that the use of range normalization can improve the training speed of a deep learning model.

5.1.2.2 Classification accuracy

In this experiment, we compared the classification accuracy of deep neural network models in classifying unseen data. We tested both deep convolutional neural network using two layer normalization techniques; batch normalization and the proposed range normalization using clinical narrative text datasets described above. We then measured the classification accuracy for each scenario. The results are shown below.

Table 5.4: Classification Accuracy

EPOCH	CNN with ResNet and Batch Normalization	CNN with ResNet and Range Normalization
0	0.908709	0.458979
1	0.999928	0.962479
2	0.999748	0.999690
3	0.999960	0.997896
4	1.000000	0.999919
5	1.000000	0.999928
6	1.000000	0.998278
7	1.000000	0.999928
8	1.000000	0.999928
9	1.000000	0.999928
10	1.000000	0.999025
11	1.000000	0.999928
12	1.000000	0.999928
13	1.000000	0.999411
14	1.000000	0.999928
15	1.000000	0.999955
16	1.000000	1.000000
17	1.000000	1.000000
18	1.000000	1.000000
19	1.000000	1.000000

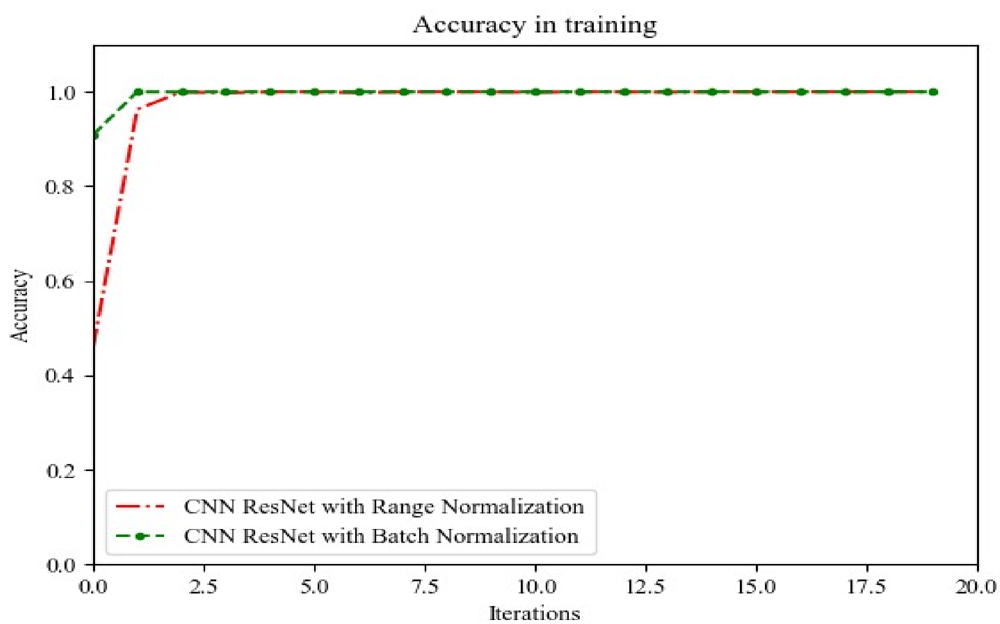

Figure 5.4: Accuracy in Training

5.1.3 Model validation using 10-fold cross validation

To analyze the performances of the four classification models (i.e. CNN ResNet with Range Normalization, CNN ResNet, CNN with Range Normalization and CNN), we performed 10-

fold cross validation. We tested the 4 types of CNN classification models using 10-fold validation with different training & validation samples. One of the 10-sub-samples is kept as validation sample and the remaining are used as training samples. For each testing, the cross-entropy loss and accuracy for training and validation are measured per epoch (total 20 epochs). After testing 10 times, the losses and accuracies are averaged per epoch to give the 10-fold cross validation results of the models. For 10-fold cross validation, all the samples have been shuffled randomly and divided into 10 sub-databases.

5.1.3.1 Training

5.1.3.1.1 Cross entropy loss

Table 5.5: 10-fold Cross Validation- Training cross entropy loss results of 4 models

Epoch	Cross Entropy			
	CNN with ResNet and Range Normalization	CNN	CNN with Range Normalization	CNN with ResNet
0	0.408686450	0.307566967	0.374406270	0.224798674
1	0.073396421	0.111671333	0.082676403	0.092680466
2	0.021309905	0.101252419	0.048192488	0.074063541
3	0.005165676	0.096796422	0.039267061	0.061435631
4	0.004758079	0.089704127	0.024219753	0.058895486
5	0.002410898	0.088045440	0.024769452	0.058013770
6	0.000689428	0.087407594	0.019293740	0.055049124
7	0.001330390	0.087136856	0.002359863	0.046755726
8	0.000505154	0.087011049	0.000422026	0.043387522
9	0.000304770	0.086886457	0.000425472	0.040270628
10	0.000142747	0.085863256	0.012481533	0.032353910
11	0.000068750	0.081506392	0.017329602	0.028412611
12	0.000047096	0.070084504	0.001921685	0.024953269
13	0.000031960	0.060171723	0.001078375	0.023653901
14	0.000020162	0.054471398	0.001706295	0.023559751
15	0.000011335	0.049273622	0.005477083	0.023538669
16	0.000522454	0.048300735	0.004897753	0.023506723
17	0.000008147	0.047965811	0.005149633	0.023496885
18	0.000005152	0.044149150	0.005634642	0.019346284
19	0.000003686	0.041965435	0.004717533	0.015296515

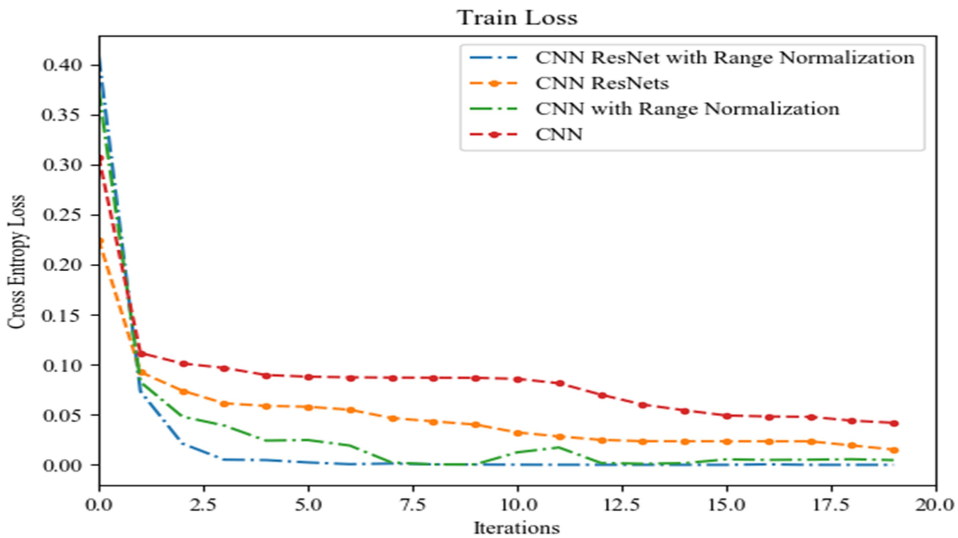

Fig 5.5: 10-fold Cross Validation- Training cross entropy of 4 models

5.1.3.1.2 Classification accuracy

Table 5.6: 10-fold Cross Validation- Training accuracy results of 4 models

Epoch	Accuracy			
	CNN with ResNet and Range Normalization	CNN	CNN with Range Normalization	CNN with ResNet
0	0.453927747	0.583580903	0.502354275	0.704545443
1	0.913722414	0.832764055	0.906586230	0.870336232
2	0.984195672	0.833281059	0.947011448	0.888091914
3	0.999651834	0.838552604	0.954737242	0.899901577
4	0.997861553	0.849710392	0.966088844	0.899914564
5	0.998285646	0.849709393	0.964705672	0.899916063
6	0.999831162	0.849712890	0.972361533	0.906505220
7	0.999394581	0.849680920	0.999126838	0.920911942
8	0.999830163	0.849652947	0.999941057	0.924951564
9	0.999892603	0.849662438	0.999843650	0.931067622
10	0.999957041	0.852661427	0.990790184	0.946068581
11	0.999986013	0.861258779	0.987402094	0.951270140
12	0.999986013	0.884097635	0.999937060	0.958406789
13	0.999986013	0.900111262	0.999746682	0.958411285
14	0.999989011	0.911330097	0.999344603	0.958410785
15	0.999997003	0.916563573	0.991457771	0.958405790
16	0.999806686	0.916590547	0.991619615	0.958410785
17	0.999999500	0.917165924	0.991404147	0.958410785
18	1.000000000	0.924931469	0.991181036	0.970250524
19	1.000000000	0.931091591	0.991621552	0.974984979

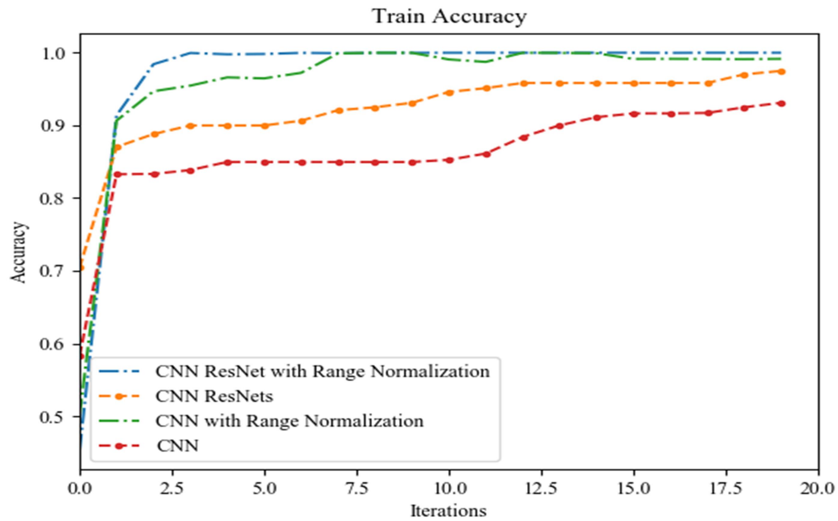

Fig 5.6: 10-fold Cross Validation- Training accuracy of 4 models

5.1.3.2 Testing

5.1.3.2.1 Cross entropy loss

Table 5.7: 10-fold Cross Validation- Testing cross entropy loss results of 4 models

Epoch	Cross Entropy			
	CNN with ResNet and Range Normalization	CNN	CNN with Range Normalization	CNN with ResNet
0	0.226155489	0.128184016	0.243999089	0.117934458
1	0.030171344	0.103873891	0.033016056	0.079316762
2	0.018833915	0.099227382	0.04344088	0.064461739
3	0.002454758	0.091532355	0.030577871	0.059659132
4	0.031807163	0.088492105	0.025710746	0.058320692
5	0.000752337	0.087571432	0.021648929	0.057763211
6	0.000498635	0.087131499	0.003330924	0.051356171
7	0.000463125	0.08700942	0.000739103	0.043834306
8	0.000229491	0.086865722	0.000347759	0.043194373
9	0.000126088	0.086774346	0.000331112	0.038310046
10	0.000158241	0.083242917	0.029418734	0.028864987
11	7.03756E-05	0.077262131	0.008442933	0.026588282
12	4.62144E-05	0.06407877	0.000908207	0.023756224
13	3.16925E-05	0.058663831	0.003406676	0.023562244
14	1.96053E-05	0.050453689	0.040955699	0.023512772
15	1.02036E-05	0.048523812	0.004921311	0.023487814
16	1.06773E-05	0.047983437	0.004818864	0.023474604
17	5.94952E-06	0.045997671	0.011892236	0.023466325
18	4.16437E-06	0.043454027	0.004696783	0.01594982
19	3.08493E-06	0.038834954	0.004662493	0.01485573

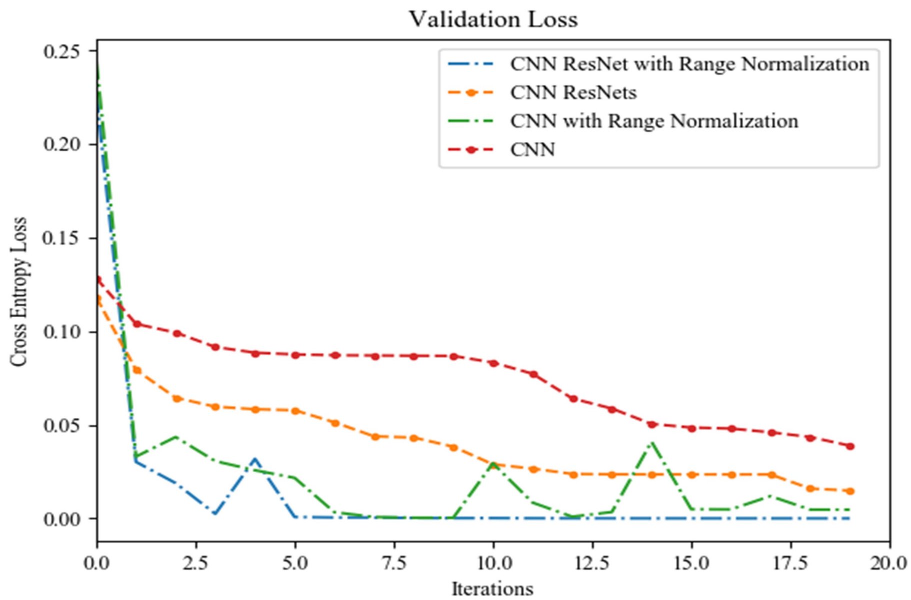

Fig 5.7: 10-fold Cross Validation- Testing cross entropy results of the 4 models

5.1.3.2.2 Classification accuracy

Table 5.8: 10-fold Cross Validation- Testing accuracy results of the 4 models

Epoch	Classification accuracy			
	CNN with ResNet and Range Normalization	CNN	CNN with Range Normalization	CNN with ResNet
0	0.729907379	0.824399781	0.670002690	0.841115901
1	0.974781942	0.833265901	0.964450145	0.883041084
2	0.992842376	0.833270395	0.941178846	0.899856120
3	0.999793184	0.849581879	0.962615770	0.899856120
4	0.951888317	0.849595368	0.963937598	0.899856120
5	0.999901086	0.849586374	0.966248542	0.899856120
6	0.999959540	0.849595368	0.998183620	0.916396904
7	0.999901086	0.849500954	0.999860620	0.924916822
8	0.999973023	0.849500954	0.999932557	0.924934804
9	0.999982017	0.849500954	0.999928063	0.933463717
10	0.999968529	0.858124274	0.974867374	0.950076431
11	0.999982017	0.872925097	0.995926625	0.958110780
12	0.999982017	0.899451488	0.999932563	0.958110780
13	0.999982017	0.899500948	0.997185504	0.958110780
14	1.000000000	0.916190094	0.956186491	0.958110780
15	1.000000000	0.916365439	0.991893715	0.958110780
16	1.000000000	0.916365439	0.991979140	0.958110780
17	1.000000000	0.924759465	0.984088665	0.958110780
18	1.000000000	0.924795431	0.991826272	0.974804425
19	1.000000000	0.946083987	0.991812789	0.974804425

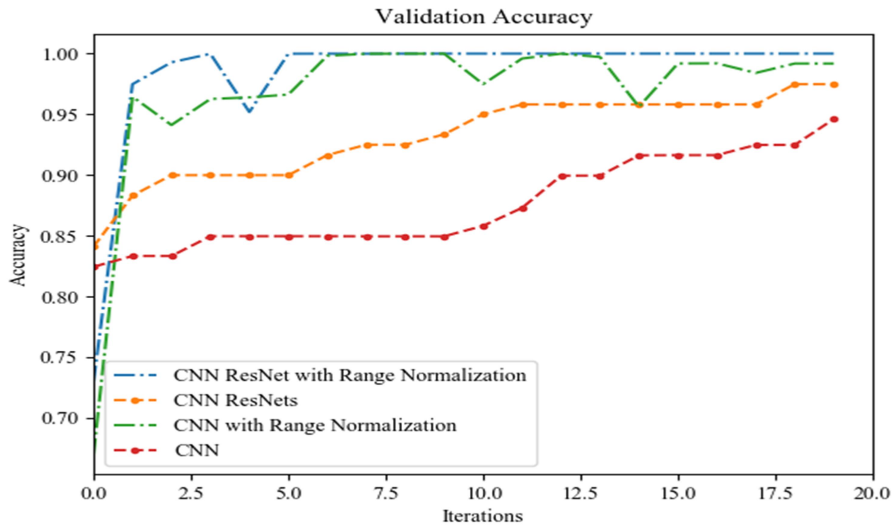

Fig 5.8: 10-fold Cross Validation- Testing accuracy results of the 4 models

As shown, the performance of CNN ResNet with Range Normalization model is better than other models; the performance of CNN with Range Normalization model is better than CNN ResNet and CNN models; the performance of CNN ResNet model is better than CNN model. We can therefore conclude that the proposed model based on deep convolutional neural network with residual connections and range Normalization has demonstrated superior performance in speed of convergence and classification accuracy and therefore important for text classification task. When using a 10-fold cross-validation method to classify the semantic classes of clinical notes, the best classifier was our proposed deep neural network with residual connections and range normalization. The results of study indicated that our CNN with residual connections based deep learning with range normalization is a promising model, which can significantly improve the diagnostic efficacy of visualising the semantic structure of a clinical document.

5.2 Evaluation of the prototype

An important part of the evaluation would be the evaluation of the artefact by clinical experts, for example general physician. In our study, we evaluated the developed artefact by subjecting it to the intended users (clinical experts) for evaluation. The prototype was made available online for use. Data collection task consisted of the following phases:

i. Users were taught how to use the visualization model,
ii. They were asked to use the model to review medical charts, and
iii. Users were asked to complete the questionnaire.

According to (Kies et al., 1998), information systems artefacts can be evaluated using three iterative stages namely; Initial design, prototype, and final design evaluations.

We evaluated the functionalities of the final artefact design with the participants as described in the sections below.

5.2.1 Quantitative Assessment

We carried out two evaluations of the final artefact design with end users:

i. The artefact usability evaluation
ii. The artefact practical application

Usability is defined by the International Standards Organization as the degree to which a product or system can be used by specific users to achieve specific goals with effectiveness, efficiency, and satisfaction in a specific context of use (ISO, 1998). Effectiveness, efficiency, and satisfaction are three components of usability (Brooke 2013) that are usually defined in relation to the context of use:

i. Effectiveness: Determines whether people can complete their tasks and meet their objectives.
ii. Efficiency: The amount of effort they put into achieving their objectives.
iii. Satisfaction: The level of confidence they have in their ability to achieve those objectives.

5.2.1.1 The System Usability Scale (SUS)

We conducted a formative user study with 12 participants to assess the usability of our artefact in supporting information retrieval from clinical narrative texts in patients' medical charts in order to gain insight into its usability. The System Usability Scale (SUS) was used in the study, which is a widely used and validated tool for assessing usability (Norman and Schneiderman 2017).

The System Usability Scale (SUS) was used to evaluate subjective reactions to the artefact in order to assess its usability for supporting information retrieval from clinical narrative texts. Brooke (1996) developed the SUS usability assessment tool for evaluating the usability of software systems. It assesses parameters such as effectiveness, efficiency, and user-friendliness satisfaction. It is a 10-question questionnaire that is rated on a 5-point scale (Bangor et al. 2009). Because it is inexpensive, it is a widely used tool for determining usability. The use of a 10-question Likert scale has the advantage of providing a broad picture of subjective usability evaluations.

It's also known as the "quick-and-dirty" usability scale because of its simplicity (Brooke 2013). We chose this instrument because of the following characteristics which makes its use attractive:

i. It is composed of only ten statements
ii. It is non-proprietary
iii. It is technology agnostic
iv. The result of the SUS is one single score (Bangor et al. 2009)

For system evaluation, data was collected using an online SUS questionnaire. The artefact was deployed online for evaluation and the participants rated the artefact by answering the questions. Each question was given a score ranging from one to five, indicating that participants rated each question on a scale of one to five, based on how much they agreed with the various statements. A score of one indicates strong disagreement, while a score of five indicates strong agreement. These values are then used to calculate the final SUS score. The SUS score is calculated as follows: the graded values for odd questions are reduced by 1, and the graded values for even questions are reduced by 5. Then after, all of the scores are added together and multiplied by 2.5. The result is a number between 0 and 100. The purpose of the questionnaire was to measure the perception of usability according to the participants' ratings. This section is therefore dedicated to research question RQ5.

5.2.1.2 SUS Evaluation Results

Table 5.9: System Usability Scale Scores

PARTICIPANT	QUESTIONS										
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SCORE
1	5	1	5	1	4	1	4	1	4	2	90.00
2	3	2	4	2	5	2	5	2	4	3	75.00
3	5	2	3	2	4	2	4	1	5	1	82.50
4	4	1	4	2	4	3	3	1	4	2	75.00
5	5	2	4	1	3	1	4	2	4	1	82.50
6	2	2	3	3	2	2	3	3	3	2	52.50
7	4	2	2	3	4	2	4	2	2	1	65.00
8	4	2	3	2	5	1	2	2	3	3	67.50
9	5	2	4	1	4	2	4	1	4	1	85.00
10	4	1	2	2	4	3	3	2	3	2	65.00
11	4	2	4	2	4	2	2	2	4	2	70.00
12	3	2	3	1	3	1	4	1	4	1	77.50
AVERAGE											**73.96**

The artefact achieved an average SUS score of 73.96 based on the preceding data, suggesting good usability. An average SUS-score of 73.96 is regarded as a satisfactory usability rating in accordance with the scale of SUS scores presented below (Bangor, A. 2009).

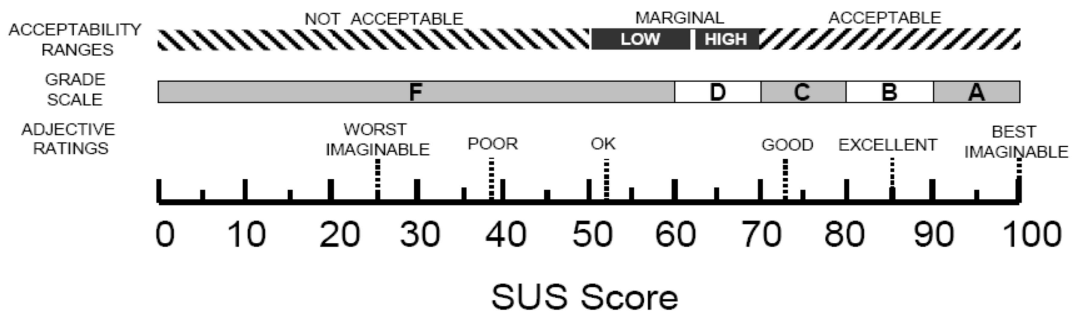

Figure 5.9: SUS Score scale: source (Bangor, A. 2009)

5.2.1.3 Utility evaluation of the artefact features

We created another questionnaire to evaluate the utility of each feature of the developed artefact in order to determine its utility. This was determined after considering the limitations of the SUS score, which only provides an overall performance score without taking into account all of the system's features. "Easy access to information in patients' medical charts" and "the usefulness of visualized information in supporting users information needs were two useful features in the proposed evaluation. The questionnaire was given to participants after giving them chance to experiment with the artefact. The goal of distributing this questionnaire was to measure the participants' feedback and opinions after they had performed the assigned tasks. The tasks provided the users the opportunity to interact with the artefact and evaluate its usefulness and utility. The feedback helped establish if the artefact is effective in supporting information retrieval from clinical narrative texts in patients' medical charts.

The first part of questionnaire pertains to the user perception on the ease of accessing relevant clinical information when performing the task of seeking information in patient's medical chart(s). The objectives of the questions were to allow the user to: judge the accuracy, completeness, and relevancy, and effectiveness, satisfaction of the presented information and whether the artefact provides creative way of structuring clinical texts to support information retrieval. The second part sought the opinions of the participants on the utility of the visualized information presented by artefact. The idea was to judge the usefulness of the artefact in reviewing patients' medical charts. This section addresses the research question RQ5.

We had 50 participants for this questionnaire. Each question had an answer option from 1-7 on the Likert scale, with 1 being completely disagree / not at all useful and 7 being completely in agreement / very useful.

Table 5.10: 7-point Likert scale

Consideration	Value
7	Strongly Agree
6	Agree
5	Moderately Agree
4	Slightly Agree
3	Slightly Disagree
2	Moderately Disagree
1	Strongly Disagree

Respondents are asked to rate a single characteristic on a Likert scale, which is a non-comparative scaling technique. Respondents are asked to use an ordinal scale to indicate their level of agreement with a given statement. Although the 5-point scale is the most commonly used, some practitioners advocate for the use of 7- and 9-point scales, which provide more granularity. Other examples include 4 point scales and even numbered scales that are used to create an ipsative (forced choice) measurement when no indifferent option is available. According to research, Likert scales with seven response options are more reliable than those with more or fewer options. Below are the results of this questionnaire.

5.2.1.4 Results Information access

The participant rating results are shown in table 5.10 and figure 5.9.

Table 5.11: Information Access evaluation

Information Access	Percentage
Relevancy	67%
Accuracy	58%
Completeness	57%
Visibility	71%
Access Effectiveness	56%
Satisfaction	53%
Creativity	75%

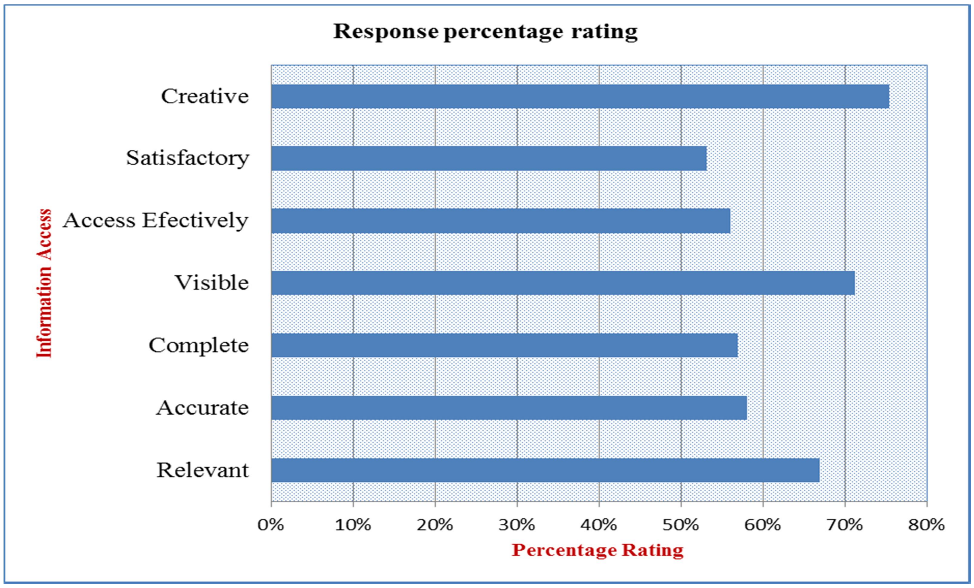

Figure 5.10: Information Access evaluation Percentage rating

The ratings of the participants achieved an average score of 62% on information access produced by the artefact. We can conclude that the artefact's information is beneficial and useful. For the most part, it is also relevant, accessible, accurate, complete, satisfactory, and creative.

5.3.1.5 Results - utility of the visualized information

The participant rating results are shown in table 5.11 and figure 5.10 below.

Table 5.12: Visual Information Percentage Ratings

Visual **Information** Utility Evaluation Survey	Percentage
Useful Summary	66.00%
Accurate summary	61.43%
Information Clarity	58.00%
Better understanding	68.57%
Time saving	62.00%
Useful format	57.71%
Medical concepts group correctly	67.43%
Privacy protection	70.29%
Research purposes	70.29%

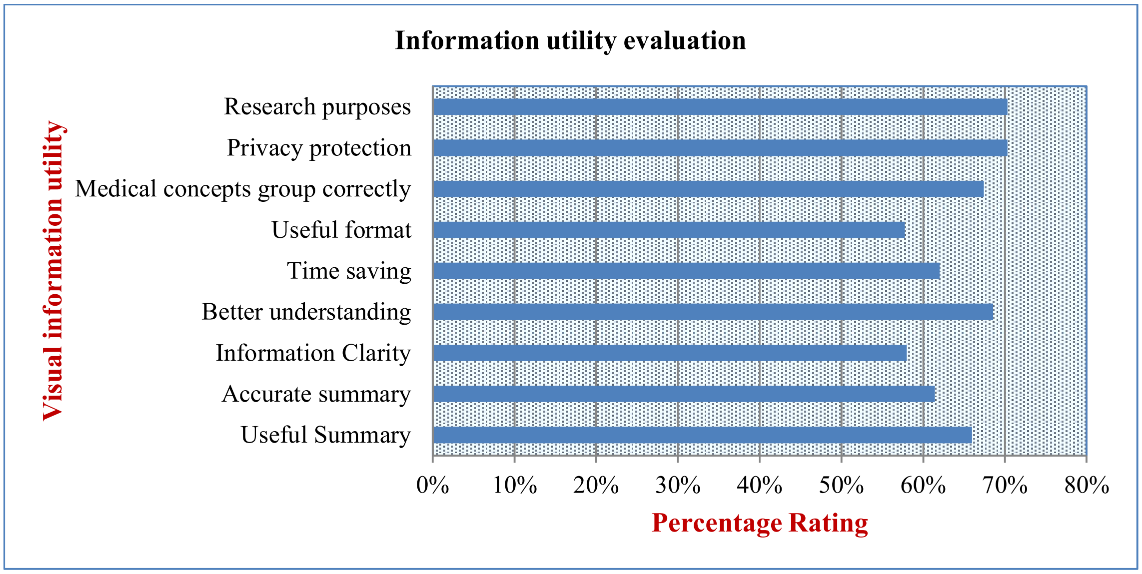

Figure 5.11: Visual information utility rating

The ratings of the participants achieved an average score of 64.64% on information utility produce by the artefact.

5.3.2 Qualitative Assessment

5.3.2.1 Survey results

The findings from this study revealed that; information needs of physicians in clinical narrative texts have many facets which include Subjective, Objective, Assessment, Plan and personal identifying information. This information was sought by physicians from clinical documentation in order to make medical decisions. The unstructured nature of clinical documentation in electronic health records was one of the problems encountered by physicians while seeking for information in various text documents. The findings of this study was useful in helping develop effective information presentation; determining the problems faced by physicians in the process of seeking information; and examining areas where physicians needed support to be able to effectively use clinical narrative texts.

From the interviews with expert users, the researcher found out that a medical chart is an important clinical document with a complete record of a patient's important clinical information and previous clinical observations (medical history). It contains data elements such as demographics, diagnoses, medications given to the patient, treatment plans, progress notes, laboratory and test results etc. Current electronic health records and other health information systems do not support comprehensive visualization of clinical documents. The researcher investigated the various uses of clinical documentation such as medical charts and the researcher found out that physicians use clinical textual documents such as patients' medical charts for different reasons:

i. Review of medical history of a patient who has received treatment previously from a different healthcare professional from the same or a different healthcare centre. This helps in obtaining a general health history of a patient. This can be necessitated by cases such as patient referral where a patient is referred to another doctor e.g. a specialist.
ii. Review of patient medical history of a returning patient. This is usually used by doctors to reacquaint themselves with a returning patient past health history. This is useful in monitoring patient's health progress. It is used as a source of information during consultation of returning patients to answer patient-related questions as health records keep a unique, individual record for each patient
iii. It is used sometimes as a legal document to ascertain the care provided.
iv. It is used to audit the process of diagnosis and treatment of a specific clinical condition.
v. It is a communication medium among healthcare professional involved in the patient's care and thus ensures continuity of care.

Therefore, physicians refer to clinical documentation for various reasons such as:

i. Establishing focus: "What are the current complaints and for what reason is this patient seeking medical care today?" (Sultanum et al, 2018)
ii. Gathering context: What is the relevant medical history for the problem(s) at hand? (Sultanum et al, 2018)
iii. Getting the gist: "What are the salient medical and psychosocial problems for this patient that I should know?" (Sultanum et al, 2018)
iv. Establishing continuity: "What happened during the last visit, and what requires follow-up?" (Sultanum et al, 2018)
v. Filling in the gaps: "What happened since the last visit, e.g., investigations or hospitalizations?" (Sultanum et al, 2018)

As a conclusion of the interviews, the researcher found out that, as electronic health records adoption in healthcare delivery increases, growing volumes of clinical documents may overwhelm physicians and therefore, there is an inevitable need for developing automated tools to support information retrieval from clinical narrative texts.

5.3.2.2 Challenges of using clinical narrative texts

Participants generally stated that it is still difficult to retrieve relevant clinical information in poorly organized information in clinical narrative texts. Future research should go into greater detail to pinpoint the precise elements of note designs that contributed to participants' perceptions that the notes were poorly organized or challenges of retrieving information. Future research should test different note designs and expand on these findings with additional user groups and EHR systems.

5.3.2.3 Analysis of information needs of physicians

A detailed information needs analysis of physicians was conducted. This was obtained using a combination of extensive interviews and analysis of clinical documentation systems such as SOAP. A taxonomy of over four information categories was identified. This information needs describe which information physicians need during care episodes. In addition, relevant clinical documentations formats were identified, and the information in each SOAP element were described. This information has been used to develop semantic classes of information which can be found in a typical patient medical chart. Also, pre-defined SOAP classes were used to aid in the classification of the clinical narrative texts.

The patient medical chart was most important and usually reviewed during care episodes. It provides the clinical history of the patient mostly in narrative form. Physicians expressed challenges with the review of electronic clinical notes, lamenting that reading them is time consuming and difficult to retrieve information from these texts. Current electronic health records present more information to the physician with no standard format. It is time to redesign the presentation of clinical narrative texts to match the information needs of physicians.

To address the problem of information overload problem which was identified in the literature, an assessment of specific information needs of physicians was conducted in order to help in understanding the relevant useful information needed by physicians to make patient care more efficient. This informed the understanding of what useful information to present to physicians when they are making clinical decisions.

From the information analysed, the most useful information needs which are frequently searched by physicians includes previous symptoms, diagnoses, disease/conclusion and treatment/therapy. Physicians need access to patient specific information in clinical notes by searching SOAP-oriented information. In addition, effective usage of previous clinical information is important for improving patient care. When making clinical decisions, doctors often seek patient information from previous medical records. Information relevant to a physician can relate to a variety of clinical information, such as symptoms, diagnosis, and treatment of a patient. In some cases, doctors can easily find the information they are looking for in patients' medical records. However, given the size of the existing records and the rapid pace at which new information is recorded, finding the most relevant and up-to-date information for a particular clinical need can be a daunting and time-consuming task. In order to make clinical patient information more accessible and to meet the requirements for a sensible use of electronic patient files, it is important to meet the needs of doctors by retrieving patient-relevant information.

5.3.2.4 Literature results

This study detailed the assessment of the use of text visualization to support healthcare delivery and research. The results show that it’s an active research field and many data visualization tools support the generation of valuable insights from patient clinical data. Furthermore, the findings demonstrate the feasibility of applying visualization tools in the clinical context. However, there is little research in the literature on the use of clinical text visualizations to meet the information needs of physicians and researchers in health care or clinical research.

5.3.3 Data Analysis

The Cronbach alpha coefficient was used in our study to see if the items in our questionnaire reliably measured the same construct (perceived task value). We took the results of a questionnaire filled out by 50 people and calculated the Cronbach's alpha coefficient based on their responses. The Cronbach's alpha coefficient was calculated for the following questionnaires:

i. Usability of the artefact (SUS questionnaire)
ii. Useful Information access
iii. Visualized information utility

A Cronbach’s alpha was calculated for the above questionnaires to test the reliability. For usability of the artefact, the Cronbach alpha was 0.821, information access, the Cronbach’s alpha was 0.819 and information utility, the Cronbach’s alpha was 0.762.

Table 5.13: Cronbach's Alpha Coefficient Analysis

Factor	Cronbach's Alpha
Usability of the artefact	0.821
Useful Information access	0.819
Visualized information utility	0.762

A statistic referred as Cronbach's Alpha is derived from the pairwise correlations between the elements. The internal consistency is between zero and one. A generally accepted rule of thumb is that the internal consistency of the scales is acceptable when α is greater than 0.7. α of 0.8 or higher indicates good reliability. High reliabilities (0.95 or higher) are not necessarily desirable as this suggests that the elements may be completely redundant. The goal in developing a reliable tool is that the results of similar elements are related (internally consistent) but also contribute some unique information.

Table 5.13 presents the Cronbach's alpha values for our data. Table 5.13 shows all the factors together with their individual Cronbach's Alpha values. The reliability of the factors is given by the Cronbach's alpha values. The factors are considered to be more reliable if their values are greater than 0.7.

5.3. Research findings

Nowadays, the importance of electronic health records is undeniable and they will continue to be more prevalent in the immediate future. This research offers a solution for modelling clinical documents using text classification and visualization techniques and is expected to addresses the inherent problems associated with clinical narrative texts. The objective is to support information retrieval from clinical text documents.

In this thesis, we presented a clinical document visualization model to visualize medical histories of patients from medical charts. A deep neural network is used to cope up with the structure of clinical documents. A set of features are extracted using convolutional neural network with residual neural connections. At the visualization step, only the necessary clinical information is displayed to the relevant user, with all personal identifying information anonymized to preserve patient privacy. Given the perceptual abilities of human beings, people, tend to easily process visual information more than textual information. The simplicity of the visualization artefact presented above is undeniably useful in extracting information in clinical narrative texts. We exposed and demonstrated our visualization model to the participants in line with the design science research methodology (Hevner et al., 2007) that advocates for rigorous evaluation of artefact using DSR methodology. The system was evaluated against initial set of requirements gathered from descriptive survey from medical practice professionals.

To examine the usability of our proposed model, we carried out an exploratory study to evaluate the practical usability of the proposed in healthcare delivery setting. We were inspired by the fact that the potential benefits of electronic health records in improving health care cannot be realized without usable systems or tools. Usability is defined as "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" (ISO, 1998). According to HIMSS (2015), a system has good usability if it is easy to use and effective.

The aim was to determine the satisfaction of the intended users with all characteristics of the artefact, namely visualization of clinical documents, ease of use, and access to information and usefulness of the information obtained. The results showed that most users were satisfied with working with the model. Most visual features were considered helpful and appropriate. Participants were helped to understand and analyse relatively small to large clinical documents and obtain summarized and visualized medical concepts. In terms of interacting with the visualization tool, study participants found the model easy to use and learn. Nonetheless, the visualization model seems to have some disadvantages, which include a lot of time needed to obtain a cluster map.

In this chapter, we describe how we have answered the research questions posed in section 1.5. , the performance of the proposed model was explored vis-à-vis the baseline algorithms' performance was discussed.

In this thesis, we have presented a privacy preserving clinical document classification and visualization model displaying a visual summary of the medical text charts of individual patients. It uses a visualization engine to display the multi-faceted clinical information by transforming it into a cluster map. The result is a graphical organization of multiple semantic classes of clinical sentences that allow rapid viewing and analysis of patient medical history.

The summary is obtained using text classification algorithm where a deep learning model is trained to learn various clinical sentences and classified them into predefined concept classes. The classified sentences are then visually display using a cluster map, which is a visual summary of a patient medical text chart.

In general, applying machine learning (Char, Shah and Magnus, 2018), (Hassanzadeh et al, 2018) and clinical data visualization is an important visual analytic tool with capability of overcoming information overload problem in healthcare (Caban and Gotz, 2015) however aapplying machine learning techniques on clinical text is always hindered by the limited labelled data available for training and testing due to health information privacy concerns and the expensive cost of expert annotations (Liang, Tsou and Poddar, 2019). Clinical documents visualization can save a substantial amount of time (Farri et al, 2012) during clinical documents review and thus help in synthesis of patient information from EHR clinical documents (Farri et al, 2012). The proposed model has sought to enable physicians to exploit large document collections. We have both sought to provide a model and thinking to physician, but have also learned about their approaches, concerns, and ways of thinking. The lessons from literature and the medical practice informed our thinking about electronic clinical data in general, and specifically the role of visual tools in aiding its use. Clinical documents visualization is an important tool for aiding discovery of useful information in electronic health data (Kenei et al, 2018), (West, Borland & Hammonf, 2014).

Clinical documents visualization could benefit healthcare delivery setting in the following ways (Kenei et al, 2018):

i. In time-constrained clinical encounters, physicians can use visualization to reduce the cognitive effort required to read through a lot of clinical narrative texts in time constraint care episodes (Farri et al, 2012), (Kvist et al., 2011).
ii. Visualizing clinical documents can aid in the identification of important information within a document and the rapid display of a set of relevant information for visual exploration (Kenei et al, 2018).
iii. Overcoming information overload problem experienced by medical professionals due to abundant availability of electronic clinical documents by providing powerful tools for patient clinical information (Rind et al, 2011).

However to effectively develop machine learning and clinical documents visualization techniques that maximize the utility of various available electronic clinical data which is collected during healthcare episodes, remains a privacy preserving problem which needs to be addressed. As explained in previous chapters, multi class classification is the most suitable technique for modeling clinical documents that involves identifying various classes of concepts in a clinical document. The proposed model for the clinical documents visualization problem adopted sentence embedding and deep learning approach which has the ability to capture word relations and therefore overcome the limitations of bag of words (BOW) representations which are usually sparse, high dimensional with the inability to capture the order as well as syntactic and semantic information of words (Kalyan and Sangeetha, 2019).

5.4 Answering the research questions

In this thesis we have focused on clinical information retrieval from clinical narrative texts, where narrative text document is structured into a visual cluster map with focus on displaying important facets of information based on SOAP clinical documentation standard. We believe that our technique presented in this thesis, can support physicians in retrieving information from clinical narrative e.g. in patients' medical charts.

The results show that it is possible to structure clinical narrative texts and visually present important clinical information available in clinical narrative texts. Physicians interviewed prefer visual summaries of patients' clinical documents instead of traditional way of going through the document manually. At the same time, they would prefer options of presenting facets of information instead of a continuous text document describing a patient health history, since the cluster map permit better abstraction of information in comparison with a continuous text document without a structure.

The main objective of this study was to develop a clinical text classification and visualization artefact which classifies clinical information according to different information facets and then displays a visual summary in form of a cluster map, hence enhancing physicians' abilities to easily review patients' clinical documents, decrease cognitive load, and potentially increase usability of clinical narrative texts. In order to attain this objective, the following five specific objectives were formulated:

i. RO1: To research on the challenges physicians face in using clinical narrative texts in electronic health records (EHRs)
ii. RO2: To investigate different types of clinical information we can infer in a corpus of clinical notes and how to model them into information facets with their inherent relationships.
iii. RO3: To design and implement classification and visualization artefact to support information retrieval from clinical narrative texts
iv. RO5: To evaluate the proposed classification model's performance against other deep learning baseline models.
v. RO4: To validate the artefact for its intended purpose over the domain of its intended applicability.

The research objectives from Chapter 1 were addressed as explained below.

i. The first objective was achieved using literature review and descriptive survey. We reviewed different challenges encountered in using digital clinical narrative texts. We found out that clinical text visualization (Sultanum et al, 2018), (Yerebakan et al, 2018) is an emerging technique to address the challenge of information overload and cognitive overload. However, there is still little research on supporting information retrieval from clinical narrative texts.
ii. The second objective was achieved using literature review and descriptive survey. Professional doctors were interviewed on the types of information they seek from electronic health records (EHRs) during encounters with patients. The results are described in chapter 3.
iii. The third objective was achieved by designing and implementing an artefact to support information retrieval from clinical narrative texts using text classification and visualization techniques.
iv. The fourth objective was achieved by carrying out a set of experiments of the proposed model classification algorithm implementation (Convolutional Neural Network with residual connections and range normalization). The different algorithms were evaluated and their individual performances were contrasted in order to fulfil the fourth objective.
v. The fifth objective was achieved by experts' intuition where the proposed model was exposed to the intended users for evaluation.

Based on the findings from chapter 5, we answered the research questions that were posed in section 1.5 in this section.

These research questions were:

i. RQ1: What are the challenges physicians encounter in using clinical narrative texts in electronic health records (EHRs)
ii. RQ2: What are the different types of clinical information we can infer in a corpus of clinical notes and how can we model them into visual information facets with their inherent relationships?
iii. RQ3: How can we build an artefact that supports information retrieval from clinical narrative texts?
iv. RQ4: Which deep learning technique can build an artefact's classification model for effective clinical text classification?

v. RQ5: How well does the developed artefact solve the stated problem and meet the defined requirements?

5.8.1 What are the challenges physicians' encounters in using clinical narrative texts in electronic health records (EHRs?)

The information overload and cognitive overload problems were identified as the main problems encountered in using clinical narrative texts. Current electronic health systems (EHRs) generate a variety of health data mostly in narrative text form, which are stored in electronic health records. Narrative text presentation makes it difficult to swiftly locate and extract necessary medical information, given the volume of texts that must be read. Clinical tasks such as reviewing clinical notes, is still manual and is an important process of making diagnostic and therapeutic decisions, however, it is still being hindered by many factors including redundant information, growing patient information with limited time to interactively review during time constraint health care delivery.

5.8.2 What are the different types of clinical information we can infer in a corpus of clinical notes and how can we model them into visual information facets with their inherent relationships

The findings from survey revealed that; information needs of physicians in clinical documents have many facets which are usually structured using a clinical documentation format such as SOAP (Subjective, Objective, Assessment and Plan). This information was sought by physicians from clinical documentation in order to make medical decisions. SOAP classes were identified to aid in the classification of the clinical narrative texts.

5.8.3 How can we build an artefact that supports information retrieval from clinical narrative texts?

To answer research question two, we designed and implemented an artefact using text classification and visualization techniques. The objective of text classification is to organize narrative texts into predefined categories that are inherently grouped according to information they convey. Text classification was achieved using a convolutional neural network with residual connections, sentence embeddings, and range normalization to classify narrative texts in a medical chart into five SOAP classes. A cluster map was then used to display the classified texts. To the best of our knowledge, this is the first study of its kind to classify and visualize clinical narrative texts to support information retrieval from clinical narrative texts.

5.8.4 Which deep learning technique can build an artefact's classification model for effective clinical text classification?

We experimented on our classification algorithm that jointly exploits sentence embeddings, deep CNN with residual connections and range normalization simultaneously. Specifically, we considered the use of range normalization in accelerating the proposed training (learning rate) and classification accuracy compared to other baselines. The performance of The proposed model achieved best learning rates and high classification accuracy thus we can conclude that the most effective learning model is the deep CNN with residual connections and range normalization simultaneously using sentence embeddings. We compared the performance of the proposed layer normalization technique to batch normalization, which is often employed to reduce internal covariate shift in deep neural network training. Our proposed normalization technique, performed well as compared to batch normalization. Thus we can fairly conclude that the deep learning design which jointly exploits sentence embeddings, deep CNN with residual connections and range normalization simultaneously is the effective learning model for classifying clinical sentences.

5.8.5 How well does the developed artefact solve the stated problem and meet the defined requirements?

The developed artefact usefulness for its intended use was evaluated, and respondents gave it good ratings. In conclusion, the artefact was found useful in supporting retrieval of information from clinical narrative texts. Clinical document classification and visualization has the potential to be used in supporting information retrieval from clinical narrative texts, according to a review by subject matter experts, and has potential to be seamlessly integrated into clinical tasks.

5.5 Chapter summary

In this chapter, an artefact based on text classification and visualization was developed to support information retrieval from clinical narrative texts. We evaluated the various classification models and identified the best classifier. Our technique shows information facets that continuously improved the identification of relevant facets of information hence supporting retrieval of information. Evaluation with users shows that the developed artefact is feasible and effective and it can be used a means to support physicians in using clinical narrative texts in electronic health records.

CHAPTER SIX: CONCLUSIONS & CONTRIBUTIONS

We summarize and conclude our work and contributions in this chapter. We'll also discuss some further research that needs to be done in the future.

6.1 Conclusion

Patient-generated health data collected in electronic health records and devices offer an opportunity for computational approaches to support medical practice and clinical research by facilitating automated retrieval of information, otherwise only possible through manual review. As the prevalence of electronic health records continues to grow, the ability to extract meaningful information from the available data is an increasingly important problem that needs to be addressed. In this thesis we investigated this problem and demonstrated how text classification and visualization can be applied to support physicians in retrieving information from clinical narrative texts. In a nutshell, our proposed artefact supports users in retrieving information from clinical narrative texts by classifying texts into various classes and visually presenting them providing intuitive display of information from clinical narrative texts. The proposed model can help users quickly get visual facets of clinical narrative texts that would otherwise take a long time to read. The success of the proposed model illustrates that a combination of text classification and visualization can be valuable in supporting information retrieval and synthesis of information from clinical narrative texts. For better information retrieval, classification and visualization are the key factors.

Computational approaches, according to this study, have the potential to:

(i) To support physicians in making medical decisions at the point of care by providing visual summaries of patient data that are easy to understand (Lee et al, 2013).

(ii) To support clinical research by summarizing huge volumes of clinical data and thus help in establishing new clinical knowledge. (Lee et al, 2013).

In general, the visualization of clinical documents is an important data analytic capability of modern health information systems (Rabelo et al., 2007; 2008) and it has the advantage of presenting a direct way to observe the documents as well as understanding the relationship between different facets on information (Cheng et al, 2009). Effective clinical document visualization is dependent on the ability to accurately identify different medical facets in clinical narrative texts. The use of convolutional neural network with residual connections was proposed due to the nature of multiple facets of medical information in clinical documents. We evaluated the classification algorithm and conducted a user study to gauge its effectiveness. The outcomes show that the proposed technique is highly effective. Our technique can save significant physician's time, as well as reduce the cognitive effort required to read through a lot of clinical narrative texts in time constraint care episodes (Farri et al., 2012). Given the time constraints during care episodes, automated tools could prove useful in providing quick and accurate information in an easily accessible form.

Our results provide the basis for more research in designing systems to visualize electronic documents using text classification and visualization techniques. Evaluation results show that text classification of clinical narrative documents achieved a high accuracy for all tested classification models. Machine learning and information visualization techniques will undoubtedly revolutionize healthcare, but given how quickly the field is evolving, we are confident that its full potential in healthcare has yet to be realized. The ability to characterize clinical information in clinical narrative texts using computational tools has significant potential.

6.2 Potential Practical Applications

An unprecedented volume of clinical data has been produced as a result of the extensive adoption of electronic health records. This creates a new challenge: successfully discovering important information from large text document collections without having to read through each document in the collection in detail. We have introduced a technique in this thesis that addresses some of the impediments to the electronic health record usage in clinical practice. The proposed artefact was created with the intention of providing users a means of reviewing patients' clinical records thus supporting informed decisions about treatment. Usually, physicians search for information in free-text clinical documents by reading through a clinical document to find segments of text that may contain relevant information. The proposed model can support this process by classifying clinical information into various semantic groups of information and presenting using a visual cluster map. It transforms clinical text document into a visual map representing the deep semantic structure of a clinical document. This will enable the user to read texts of pertinent information clusters to retrieve the information needed.

Our proposed approach is anticipated to solve some of the issues that the study's findings revealed, including:

i. Lessening the cognitive load caused by large volumes of clinical documents and time-constrained patient encounters, resulting in better clinical decision-making.

ii. Alleviating the problem of information overload caused by the availability of detailed clinical patient information, often in an unstructured format. It can assist the doctor in conducting a more thorough review of the patient's medical history and making more informed treatment decisions.
iii. Aiding in the efficient organization of clinical narrative texts. Rather than reading a document in a linear manner, the information is presented in various semantic clusters.
iv. Supporting information retrieval when narrative texts are segmented by information classes, one can easily extract needed information from respective cluster.
v. Supporting readability by decomposing a long narrative text document into smaller-clusters of information so it is easier for the reader to consume. A clinical narrative text need to be decomposed and structured into fine-grained information facets in order to focus on individual facets more closely.

6.3 Contributions

According to Aigner, Kaiser and Miksch (2008), the growing use of health information systems in healthcare is increasing the volume and complexity of detailed patient data available to physicians. In this study, a document classification and visualization artefact was developed as a proof-of-concept to visualize clinical narrative texts stored in electronic health records. An empirical study was conducted with the aim of gathering physicians' opinions on the visualization of clinical narrative texts. The qualitative and quantitative results obtained from usability studies showed preference for using the proposed model in navigating a patient's medical record to retrieve pertinent clinical information. This research has made a number of contributions regarding clinical documents classification and visualization. The significant contributions we made are listed below:

6.3.1 Theoretical Contributions

We proposed a clinical document classification and visualization model that can be used in healthcare delivery to speed up information retrieval in the decision-making task. Though this model was evaluated by physicians, it is expected that it could also be applicable to other purposes such as clinical research. The model suggests the use of deep learning model in classifying medical concepts; then applying range normalization to improve the learning rate. From the literature, there is little literature to support the use of health data visualization to improve the quality of healthcare delivery. Therefore, we have built the literature describing the use of text visualization to process clinical documents.

6.3.2 Methodological Contributions

Our contribution is that we have introduced the join use of text classification and visualization in identifying a document's semantic classes of information and organizing them into a visual cluster map structure. This is expected to aid in understanding the semantic structure of a document which will not only support in information retrieval but also enable users to quickly navigate to classes of information of interest. We have used the semantic classes based on SOAP documentation standard (from a conceptual perspective) to solving clinical documents classification problem and introduced a novel clinical document visualization technique for retrieving and exploring patients' clinical charts.

6.3.3 Technical Contributions

In this work we introduced a novel artefact for structuring narrative texts using text classification and visualization. In this thesis we have presented a technique for supporting information retrieval from clinical narrative texts through a visual interface based on automatically generated cluster map. We used a deep learning algorithm to classify clinical texts into a set of information facets. Additionally, the classified clinical texts were visualized in a cluster map layout to depict the various facets and the relationship among the facets. The resulting graph layout serves as an aid to users for retrieving documents. Users can then retrieve information more easily with the help of the visual interface. To the best of our knowledge, this is the first work that has applied text classification and visualization to structure and visualize clinical narrative texts to help in extraction and retrieval of information. From the experimental results, our technique based on range normalization performed well compared to other models. In particular our unique contribution is applying sentence embeddings and neural networks with residual connections and range normalizations simultaneously. This is the first time, to our knowledge, that range normalization has been used to normalize layer inputs.

6.4 Future Work

The findings reported in this study can be expanded in a variety of ways. This includes expanding to other clinical text documents and even non-medical documents and researching the best deep learning technique for classifying sentences. Given the utility of visualization by healthcare professionals identified in this thesis, evaluation with a larger target audience is recommended to ensure that the results are valid for a wider community of healthcare professionals. It is also recommended to experiment with different types of clinical documents to ascertain if similar results can be achieved. More research with these users is needed to expand on the research that has already been done and presented in this thesis. Extending current research to areas other than health would also be worth looking into to see if the proposed method can be applied to other fields to demonstrate its generality.

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APPENDIXES

Appendix I: System Usability Scale (SUS) Form

System Usability Scale (SUS) Form

Name: --

Gender: ☐ Male ☐ Female

Age: -------------

Education Level

- ☐ Professional training
- ☐ Bachelor
- ☐ Master
- ☐ Doctorate
- ☐ Other:

Knowledge of Electronic health records*

- ☐ Basic
- ☐ Intermediate
- ☐ Advanced
- ☐ Expert
- ☐ Other:

Instructions

Based on your experience using clinical, check the box that reflects your immediate response to each statement. Don't think too long about each statement. Make sure you respond to every statement. If you don't know how to respond, simply check box "3".

		Strongly disagree 1	2	3	4	**Strongly agree** 5
1	I think that I would like to use this system frequently	☐	☐	☐	☐	☐
2	I found the system unnecessarily complex	☐	☐	☐	☐	☐
3	I thought the system was easy to use	☐	☐	☐	☐	☐
4	I think that I would need the support of a technical person to be able to use this system	☐	☐	☐	☐	☐
5	I found the various functions in this system were well integrated.	☐	☐	☐	☐	☐
6	I thought there was too much inconsistency in this system.	☐	☐	☐	☐	☐
7	I would imagine that most people would learn to use this system very quickly	☐	☐	☐	☐	☐
8	I found the system very cumbersome to use	☐	☐	☐	☐	☐
9	I felt very confident using the system.	☐	☐	☐	☐	☐
10	I needed to learn a lot of things before I could get going with this system	☐	☐	☐	☐	☐

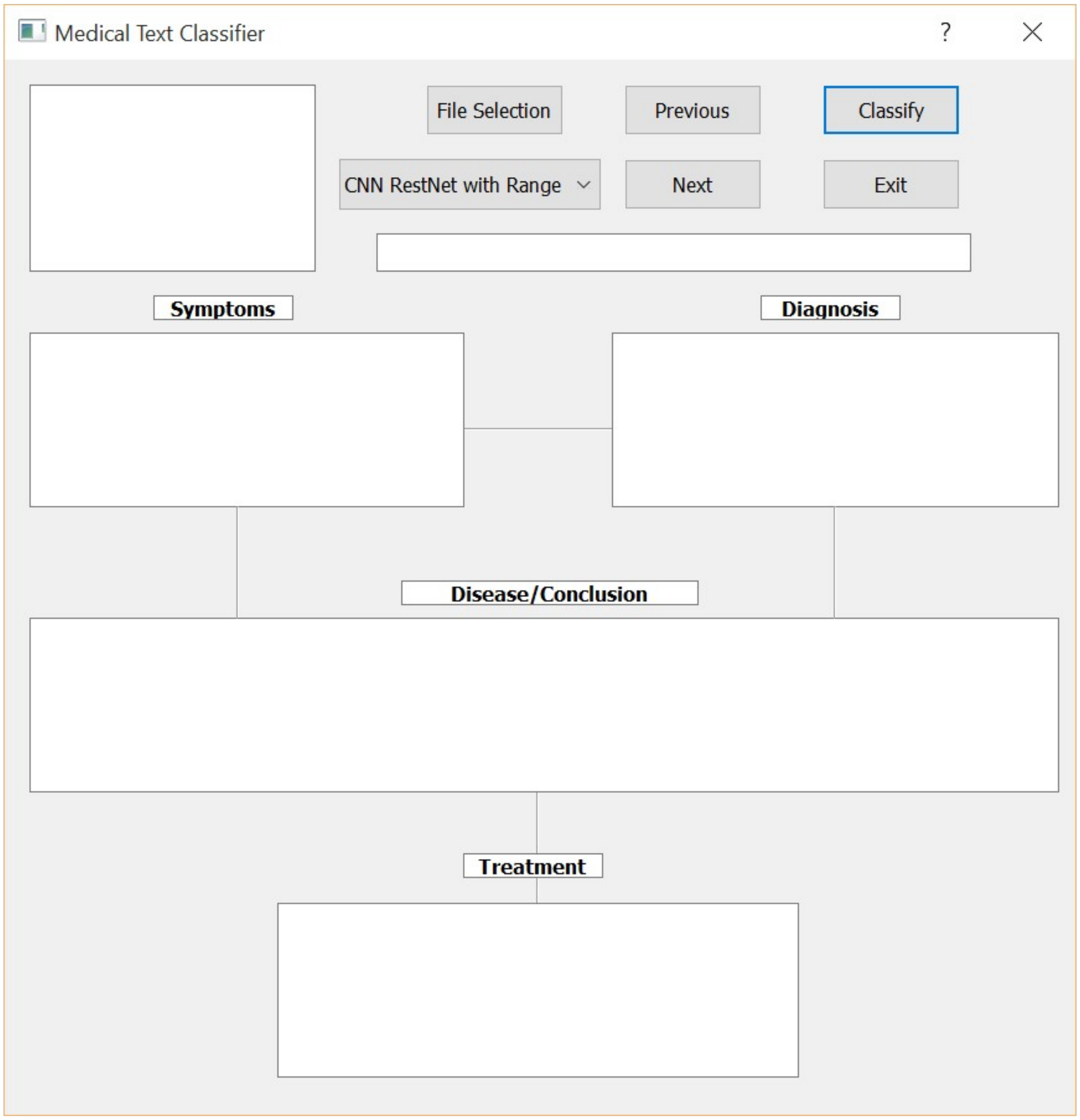
	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
A. INFORMATION					
1. Information I get from the model is relevant to my work.	1	2	3	4	5
2. Information I get from the model is accurate.	1	2	3	4	5
3. Information I get from the model is complete.	1	2	3	4	5
4. Required information is easily visible.	1	2	3	4	5
5. I can access information I need effectively.	1	2	3	4	5
6. While using this interactive chart, I found satisfactory.	1	2	3	4	5
7. In general, I think this is a creative way of summarizing medical charts	1	2	3	4	5
B. UTILITY					
1. If the visualization model was put into practical use, I would like to use it because of rich information	1	2	3	4	5
2. The visual summary accurately summarizes and medical chart and clustering related concepts.	1	2	3	4	5
3. The visual summary clearly displays all the required.	1	2	3	4	5
4. In general, I think the model allows me to better understand patients' clinical history and me to improve diagnosis process.	1	2	3	4	5
5. In general, I think using the model may save me time, compared to the way I currently review clinical documents in either electronic or paper-based forms.	1	2	3	4	5
6. The information is presented in a useful format.	1	2	3	4	5
7. The visual summary has clustered medical concepts correctly.	1	2	3	4	5
8. Personal identifying have been correctly de-identified(anonymized)	1	2	3	4	5
9. The model can be deployed for research purposes without concern for privacy violations.	1	2	3	4	5

Results - Information access								
Questionnaire Questions								
Respondent	**Q.1**	**Q.2**	**Q.3**	**Q.4**	**Q.5**	**Q.6**	**Q.7**	**Total**
R.1	2	3	4	7	4	3	5	23
R.2	3	4	3	5	3	3	5	21
R.3	3	3	1	5	4	3	5	19
R.4	3	4	3	4	3	4	5	21
R.5	3	3	4	6	3	3	5	22
R.6	3	3	2	5	4	4	3	21
R.7	3	2	2	4	3	3	4	17
R.8	4	2	3	4	2	2	7	17
R.9	4	3	3	6	4	4	6	24
R.10	4	1	4	5	4	4	4	22
R.11	4	5	4	4	6	2	5	25
R.12	4	3	4	3	4	4	5	22
R.13	4	3	2	4	3	2	4	18
R.14	4	2	3	4	2	3	6	18
R.15	4	4	4	4	4	4	7	24
R.16	4	1	4	5	3	3	5	20
R.17	4	3	3	5	3	3	4	21
R.18	4	2	3	4	2	4	7	19
R.19	4	3	3	2	4	3	6	19
R.20	4	2	4	5	4	3	4	22
R.21	4	7	4	4	2	4	3	25
R.22	4	5	2	5	4	2	2	22
R.23	4	2	4	4	3	4	6	21
R.24	4	2	2	5	4	4	5	21
R.25	4	4	5	4	3	3	6	23
R.26	4	3	3	4	7	3	4	24
R.27	4	5	3	6	4	3	4	25
R.28	5	4	6	5	4	3	3	27
R.29	5	4	6	7	2	3	5	27
R.30	5	2	3	6	2	1	4	19
R.31	5	2	3	2	5	5	7	22
R.32	5	4	4	5	5	4	7	27
R.33	5	7	4	6	3	4	7	29
R.34	5	7	4	5	4	4	2	29
R.35	5	7	4	4	3	4	4	27
R.36	5	5	3	7	4	6	7	30
R.37	5	4	4	4	5	5	6	27
R.38	5	4	4	5	4	4	5	26
R.39	5	6	4	5	3	5	7	28
R.40	6	4	5	5	4	4	7	28
R.41	6	4	6	5	6	4	7	31
R.42	6	6	6	7	5	5	5	35
R.43	7	7	6	7	5	6	7	38
R.44	7	7	6	7	5	6	6	38
R.45	7	4	7	7	5	6	6	36
R.46	7	6	6	7	4	6	6	36
R.47	7	7	6	5	5	2	6	32
R.48	7	6	6	5	7	4	6	35
R.49	7	6	4	5	5	4	6	31
R.50	7	6	6	5	5	4	6	33
Totals	234	203	199	249	196	186	264	1267
Var	1.691429	3.16	1.898	1.489	1.463	1.308	1.879	11.01
K	6							
∑Var	11.009							
Var	32.882							
Cronbach's alpha =	**0.798252**							

4.4.2.2 Results - utility of the visualized information

	Questionnaire Questions								
Respondent	Q.1	Q.2	Q.3	Q.4	Q.5	Q.6	Q.7	Q.8	Q.9	Total
R.1	6	3	4	5	4	5	5	7	4	27
R.2	7	4	3	4	3	5	4	6	5	26
R.3	5	3	6	2	2	5	4	6	4	23
R.4	7	4	3	4	3	5	4	6	5	26
R.5	5	3	4	4	3	5	5	5	4	24
R.6	7	5	2	5	4	5	3	6	5	28
R.7	5	5	4	7	3	5	4	6	4	29
R.8	3	5	5	7	2	5	5	7	7	27
R.9	5	5	3	7	4	4	4	4	7	28
R.10	3	4	4	5	4	4	3	3	3	24
R.11	4	3	4	4	2	6	5	5	7	23
R.12	4	3	4	3	4	6	4	4	5	24
R.13	4	4	3	6	3	7	4	4	5	27
R.14	5	4	5	6	2	7	7	5	6	29
R.15	4	4	3	6	6	4	7	5	7	27
R.16	4	3	4	5	3	7	7	6	7	26
R.17	4	7	3	5	3	4	7	5	7	26
R.18	5	7	5	4	2	4	5	4	4	27
R.19	5	5	3	3	7	3	5	4	4	26
R.20	4	3	4	5	4	3	6	5	6	23
R.21	4	4	4	4	2	4	6	5	6	22
R.22	4	3	6	5	4	2	4	4	4	24
R.23	4	3	4	4	3	5	5	5	5	23
R.24	5	4	2	5	4	5	5	5	5	25
R.25	4	4	2	4	3	4	4	4	4	21
R.26	4	5	3	4	2	4	5	5	5	22
R.27	5	4	3	2	7	2	4	4	4	23
R.28	4	4	4	3	7	3	4	5	5	25
R.29	4	6	4	4	6	4	3	7	3	28
R.30	5	3	3	4	6	3	5	3	3	24
R.31	5	3	3	3	7	4	4	4	4	25
R.32	7	3	4	5	7	3	5	5	5	29
R.33	4	4	4	4	1	3	3	3	3	20
R.34	4	4	2	5	4	3	4	4	4	22
R.35	4	3	5	4	6	4	5	5	5	26
R.36	5	6	3	6	5	4	5	5	5	29
R.37	7	2	3	6	5	3	4	6	4	26
R.38	1	5	7	6	5	3	2	6	4	27
R.39	3	6	1	7	5	7	6	5	4	29
R.40	5	5	2	7	5	3	4	2	4	27
R.41	7	6	3	4	4	3	5	5	5	27
R.42	4	5	7	6	5	1	7	6	7	28
R.43	2	5	6	7	5	3	6	4	7	28
R.44	2	6	7	5	6	7	5	5	6	33
R.45	5	5	7	5	6	4	4	6	5	32
R.46	4	4	6	6	6	3	5	4	6	29
R.47	7	6	5	6	7	3	5	5	3	34
R.48	7	4	7	2	5	1	4	4	4	26
R.49	4	4	4	5	5	2	5	6	6	24
R.50	5	5	6	5	6	3	5	6	5	30
Totals	231	215	203	240	217	202	236	246	246	1308
Var	1.873061	1.357143	2.302449	1.795918	2.759592	2.202449	1.266939	1.177143	1.503673	12.29061
K	9									
∑Var	16.23837									
Var	8.708571									
Cronbach's alpha =	0.88412									

Appendix II: Selected Source Code



Appendix III: Sample Test Screen Shots

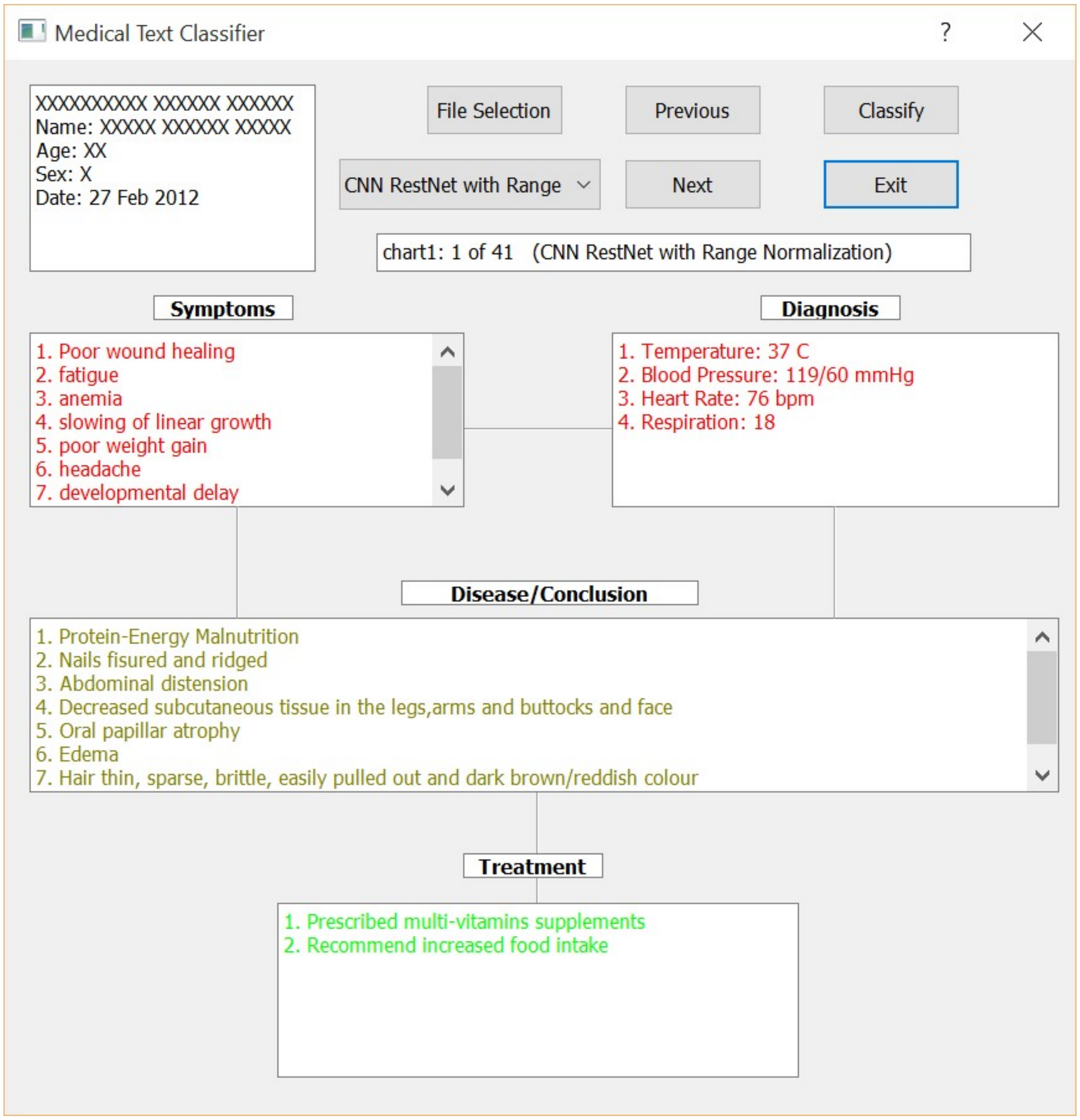
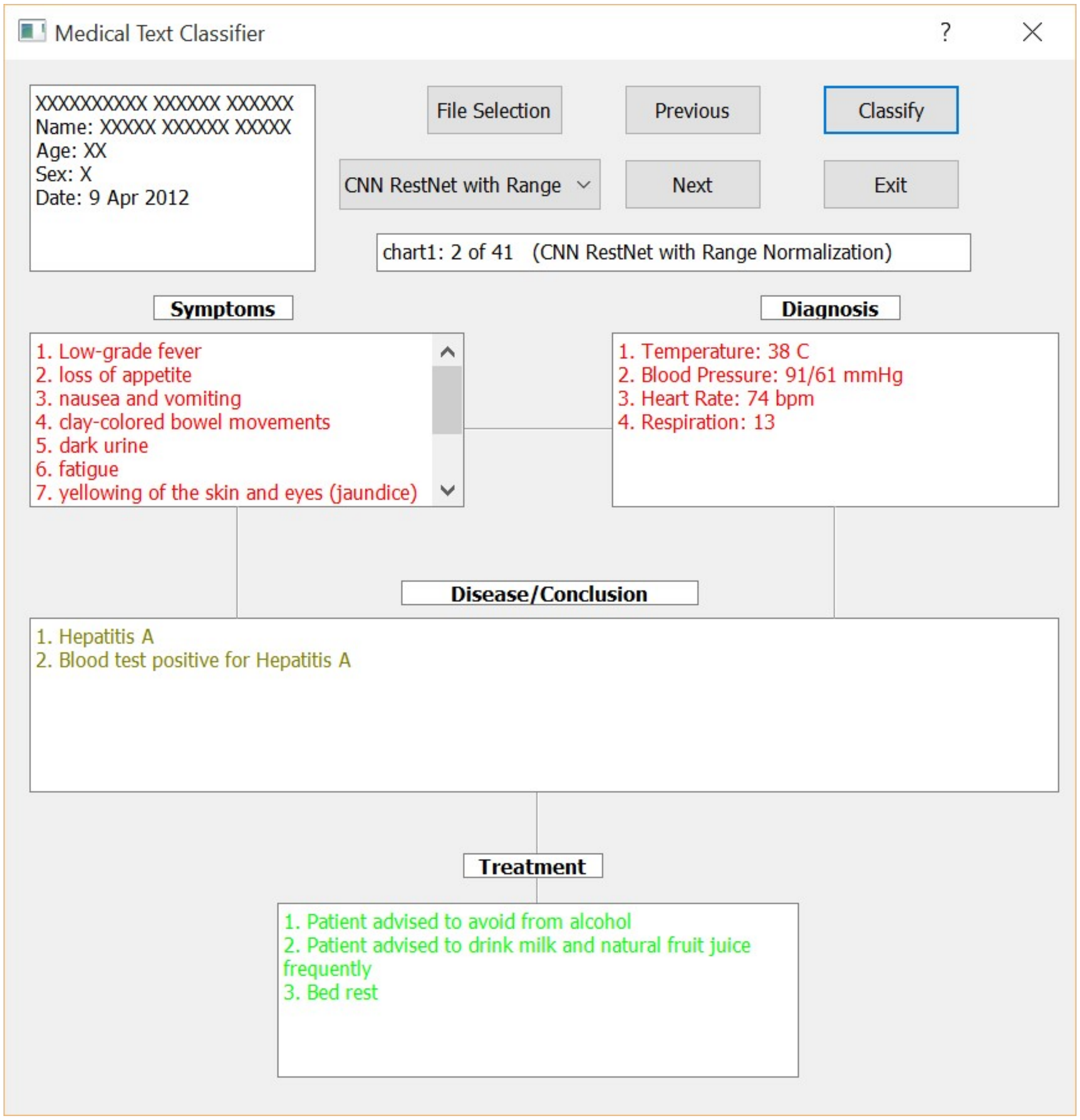
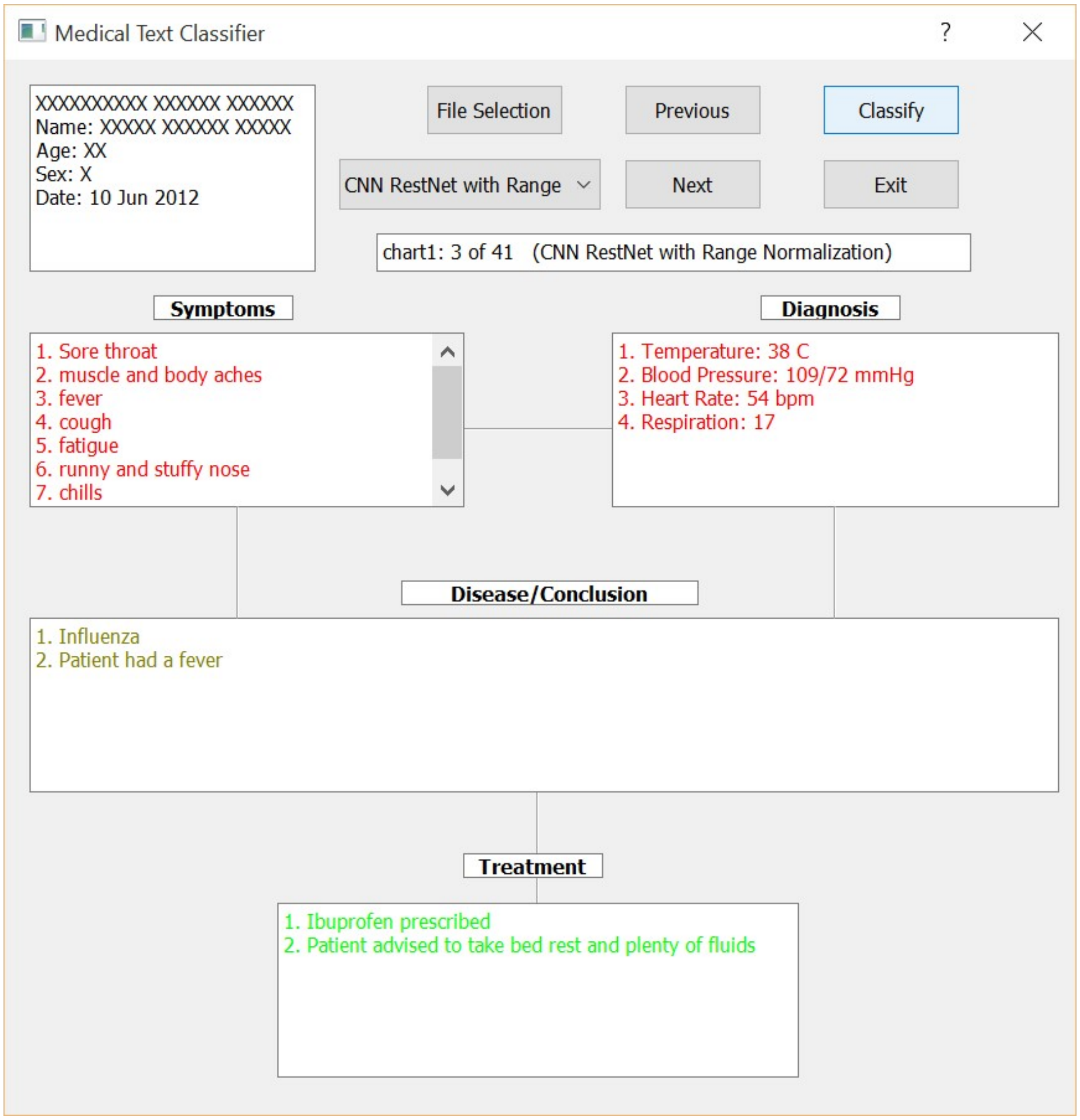


Figure 6.1: Temporal layout for a single patient visit


Medical Text Classifier
XXXXXXXXXX XXXXXX XXXXXX
Name: XXXXX XXXXXX XXXXX
Age: XX
Sex: X
Date: 9 Apr 2012
File Selection
Previous
Classify
CNN RestNet with Range
Next
Exit
chart1: 2 of 41 (CNN RestNet with Range Normalization)
Symptoms
1. Low-grade fever
2. loss of appetite
3. nausea and vomiting
4. clay-colored bowel movements
5. dark urine
6. fatigue
7. yellowing of the skin and eyes (jaundice)
Diagnosis
1. Temperature: 38 C
2. Blood Pressure: 91/61 mmHg
3. Heart Rate: 74 bpm
4. Respiration: 13
Disease/Conclusion
1. Hepatitis A
2. Blood test positive for Hepatitis A
Treatment
1. Patient advised to avoid from alcohol
2. Patient advised to drink milk and natural fruit juice frequently
3. Bed rest


Medical Text Classifier
XXXXXXXXXX XXXXXX XXXXXX
Name: XXXXX XXXXXX XXXXX
Age: XX
Sex: X
Date: 10 Jun 2012
File Selection
Previous
Classify
CNN RestNet with Range
Next
Exit
chart1: 3 of 41 (CNN RestNet with Range Normalization)
Symptoms
1. Sore throat
2. muscle and body aches
3. fever
4. cough
5. fatigue
6. runny and stuffy nose
7. chills
Diagnosis
1. Temperature: 38 C
2. Blood Pressure: 109/72 mmHg
3. Heart Rate: 54 bpm
4. Respiration: 17
Disease/Conclusion
1. Influenza
2. Patient had a fever
Treatment
1. Ibuprofen prescribed
2. Patient advised to take bed rest and plenty of fluids